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The Gender Labor Market Gap in the Digital Economy*

Monserrat Bustelo Luca Flabbi Mariana Viollaz

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Abstract

Recent years have seen an ever-greater expansion of the *digital economy*, a development that may bring new opportunities to workers who were at a disadvantage in the traditional economy. We focus on a specific set of workers who belong to such a group: women. We study a skill set of particular relevance in the digital economy and estimate their returns in the labor market, according to gender, across four Latin American countries. We find that information and communication technologies (ICT) skills and science, technology, engineering, and mathematics (STEM) skills yield significant positive returns for both men and women. However, there is a significant gender gap that favors men on the STEM returns. There is also a sizable gender gap regarding the amount of skills accumulated by gender. Through an Oaxaca-Blinder decomposition, we estimate that up to 80% of the gender gap in hourly wages may be due to the lower returns that women receive, relative to men, on their STEM skills. If an investment in skills relevant to the digital economy may be beneficial for the labor market performance of both men and women, why returns to STEM exhibit such strong gender asymmetries remains an open and relevant question.

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The paper also includes a Web Appendix available at https://sites.google.com/site/lucaflabbi/home/research/BusteloFlabbiViollaz2019_OnlineAppendix.xlsx?attredirects=0&d=1.

1 Introduction

1.1 Motivation

Recent years have seen major changes in global labor markets. Technical innovation is leading to changes in industrial structure, workers' productivity, and the process of matching workers' skills with firms' technology. This is the result of the ever-greater expansion of a *digital economy*, in which old jobs are lost, new jobs are created, and even the same jobs are approached differently and require different competences. If old jobs are lost but new ones are created, then new opportunities may arise for workers who were previously at a disadvantage in the traditional economy.[1]

In this paper, we focus on a specific set of workers who belong to such a group: women. Gender gaps in the labor market have been a significant and persistent empirical regularity in most countries around the world (Blau and Kahn, 2017). The digital economy affects this longstanding gap and may act to reduce or magnify it, depending on the skills that men and women can acquire and deliver in the labor market. Focusing on a set of high-income countries, OECD (2018a) finds that differences in skill endowments between male and female workers account for some but not all of the wage gap. When controlling for skills relevant to the digital economy, the gender wage gap is reduced by 1 to 12 percentage points.[2] OECD (2018b) also shows evidence of gender gaps in skills, tracing some back to human capital acquisition during the schooling years. However, among recent generations, the study finds that the gender gap in skills relevant to the digital economy is more ambiguous: In some areas, girls outperform boys (e.g., collaborative problem solving) but are outperformed by boys in others (e.g., digital-related skills).

Our report focuses on Latin American countries where no systematic analysis of the interaction between the digital economy and the gender gap has been undertaken.[3] The primary reason for the

[1] A number of reports by multilateral organizations and international think-tanks are making a similar point: for the OECD, see OECD (2018a; 2018b); for the World Bank, see Box 2.10 in World Bank (2016); for the ILO, see Ryder (2018); for the WEF, see World Economic Forum (2018); for the IDB, see Busso et al. (2017).

[2] See Section 1.3 in OECD (2018a). The highest reduction is for Japan, which has the highest gender wage gap among OECD countries at about 40%.

[3] Some country reports are starting to look at gender differences in skill acquisition, but without relating the results to gender differentials in the labor market. See, for example, OECD (2016) on Chile. The report – using PIAAC data –

absence of systematic contributions across Latin America relates to data limitations: Representative individual-level data, capable of capturing the skills required in the digital economy, are scarce. We are taking a first step in this analysis by using data sets comprising this relevant information for four Latin American countries: Chile, Bolivia, Colombia, and El Salvador. We have obtained the relevant information by combining two different surveys that collected data on skills: the *Programme for the International Assessment of Adult Competencies* (PIAAC) survey, available for Chile in 2014, and the *Skills Towards Employment and Productivity* (STEP) survey, available for Colombia and Bolivia in 2012 and for El Salvador in 2013.

After extracting the estimation sample, we document gender gaps in skills endowments and estimate returns to skills. We control for a variety of factors, including heterogeneous returns by workers' human capital and by sectors' digital intensity. We check the robustness of the results, with respect to the endogenous selection of women in the labor market. Finally, we decompose the gender gap in the portion resulting from differences in returns to skills and differences in skill endowments.

Two specific skills yield significant returns across the board: STEM (*science, technology, engineering, and math*) and ICT (*information and communication technologies*). ICT returns are similar across genders, with an increase of one standard deviation in the skill generating a return in hourly wages of about 17%. By contrast, STEM returns differ significantly between genders, with an increase of one standard deviation generating a 15% return for men and a 9% return for women. Results by country show some differences in magnitudes. Returns to STEM are higher than the aggregate in Chile and lower than the aggregate in Bolivia, Colombia, and El Salvador. We also estimate that higher levels of education imply significantly higher returns for men but not for women. The estimates indicate that STEM endowments and returns play an important role in explaining the aggregate gender gap in hourly wages; the lower endowments for women may be responsible for up to 30% of the gap, while the lower returns for women may account for close to 80%.

finds that "men outperform women in both literacy and numeracy. These gender gaps are among the widest observed across OECD countries" (page 6). Busso et al. (2017), on study skill formation in the Latin American and the Caribbean region, provided evidence on the availability and adoption of digital technologies but not on their relation to the gender gap.

1.2 Structure

The paper is organized as follows: Section 2 describes the data and the specific indicators we build to describe the digital economy. Section 3 provides standard descriptive statistics on the gender gaps in the labor market, integrating gaps in skills relevant to the digital economy. Section 4 provides estimates of the returns to these skills, according to gender. The estimates control for a rich set of individual characteristics and, in some specifications, for selection in the labor market. We also provide evidence regarding the interaction of the skills with the sectors most exposed to the digital economy, as well as with education levels. Section 5 focuses on the gender gap in hourly wages and unpacks the extent to which the gap can be accounted for by differences in returns, relative to differences in the endowment of digital-economy-relevant skills. Section 6 provides final comments and a summary of the results. Appendix A includes details about the construction of the variables of interest, Appendix B presents the complete regression results, and Appendix C provides results according to country. A Web Appendix includes additional specifications and robustness checks.

2 Data

We combine information from two surveys that collected data on skills at work. First, we use information accessible in the PIAAC survey, available for Chile in 2014. The PIAAC is a survey of adult skills, collected by the OECD, which measures adults' proficiency in key information-processing skills – literacy, numeracy, and problem solving – and gathers data on how adults use their skills at work. The survey is implemented by an international consortium, contracted by the OECD, and is designed to ensure international comparability of the data. Second, we use information from the STEP survey, available for Colombia and Bolivia in 2012 and El Salvador in 2013. STEP is a survey collected by the World Bank and gathers data on skills in urban areas of low- and middle-income countries. It also shares the main objectives and structure of the PIAAC questionnaire. It strives to record the data in a way that renders it comparable across different countries.

Still, two concerns remain regarding the comparability of STEP and PIAAC for our purposes. The first relates to differences in sampling: STEP is representative of people aged 15-64, living in urban

areas, while PIAAC is representative of people aged 16-65, living in both urban and rural areas. Due to STEP's urban focus, we exclude from the estimation sample workers employed in sectors represented more heavily in non-urban areas: agriculture, forestry and fishery, as well as mining and quarrying.[4] Due to the slightly disparate age range between the two surveys, we include individuals aged 16-64 in the estimation sample. We also restrict the sample to wage employees of the private sector, except for El Salvador, where it is not possible to distinguish between the private and public sector. These restrictions generate a final estimation sample with 1,541 observation for Chile, 510 for Bolivia, 668 for Colombia, and 522 for El Salvador.

The second relates to differences in survey questions. PIAAC and STEP use different questionnaires to collect information. Still, the questions about labor market outcomes, demographic characteristics, socioeconomic variables, and ability measures generate variables that allow for a high degree of comparability between the surveys. The differences in survey questions become more relevant when crafting measures of skills, as eliciting skills is a more difficult, and arguably less agreed upon, task than eliciting demographic characteristics or standard labor market outcomes and, because skills are at the center of the paper's contribution. For these reasons, we devote the next section of the paper to describing how we build the relevant skills measures from the surveys' questions and implement a procedure to maximize comparability across countries and surveys.

Throughout the paper, the unit of observation of the data remains the individual worker. The level of analysis operates at both the country level and the aggregate level, pooling all countries into a single data set. Typically, we discuss the results from the pooled sample in the main text of the paper and report country-level results in the Web Appendix.

[4] We could not limit our direct focus to the urban population in Chile because PIAAC does not report an indicator for urban and rural areas. The only geographic indicator reported by PIAAC is the OECD territorial level 2 region, which, for Chile, corresponds to 11 of the 15 regions of the country. We have combined this information with the rural/urban indicator contained in a nationally representative household survey for Chile – the 2013 CASEN survey. Based on CASEN, we can calculate the proportion of the population in each region living in urban areas. Results show that most of the population in each Chilean region is concentrated in urban centers. In most of the regions, more than 90% of the population lives in urban areas, with the most rural region (Maule) reporting 67% of urban population. Still, we have performed a robustness exercise, where we eliminated regions with less than 85% or 75% of the population living in urban areas. Our results were barely affected.

2.1 Skills measures

We build the skills measures to summarize the information collected in the numerous relevant survey questions and in order to maximize the comparability with previous literature and across countries. We focus on skills relevant in the digital economy. The previous literature has identified ICT and STEM quantitative skills as critical to thriving in the digital era (OECD, 2018a; OECD, 2018b). It has also argued that soft, social, and interpersonal skills, jointly with creativity and critical thinking, will become critical in future, innovative labor markets (Ryder, 2018; World Economic Forum, 2018; OECD, 2018b). To capture both sets of competencies, we follow the classification proposed by Grundke et al. (2017) in preparatory work for a series of OECD reports on skills and the digital economy.[5] They define the following six sets of skills using data from the PIAAC survey on OECD countries:

1. *ICT skills* are those related to ICT use, from reading and writing emails to using Word and Excel or a programming language.

2. *Managerial and communication skills* capture strategic management abilities for the generation of sustainable competitive advantages, including human resource management practices, which encompass negotiating with people, instructing, advising, and persuading people.

3. *Readiness to learn and creative problem-solving skills* include the ability to solve problems in the process of developing organizational capabilities and improving firm performance.

4. *Self-organization skills* capture workers' flexibility to adapt to changes and absorb shocks.

5. *Marketing and accounting skills* include abilities associated with accounting tasks, such as reading financial invoices and bills, and with front-of-office marketing tasks, such as interacting with clients.

6. *STEM quantitative skills* include the ability to apply algebra, simple or complex, and prepare charts and tables.

In Table A1 in Appendix A, we provide details on the exact questions from PIAAC and STEP that we use to generate each skill measure and the metric associated with each variable. Variables from

[5] See OECD (2018a, 2018b).

PIAAC derive exactly from the definition proposed by Grundke et al. (2017): We construct the same set of measures using the PIAAC for Chile as they did using the PIAAC on the 31 OECD countries in their analysis.[6] In the STEP surveys for Bolivia, Colombia, and El Salvador, we identify the questions aimed at capturing the same skills and that are as close as possible to those available in PIAAC.

The first important difference between the two surveys is that most variables in PIAAC capture the frequency of doing certain task (from "never" to "every day") through categorical variables, while STEP involves a combination of binary questions (whether a person performs a certain task at work or not) with some categorical frequency questions as in PIAAC. In order to overcome these differences between surveys, we construct the skill measures applying a standardization methodology used by previous studies (Acemoglu and Autor, 2011; Almeida et al., 2018). First, for each variable associated to a skill category, we calculate the mean and standard deviation and standardize the variable by subtracting the mean and dividing by the standard deviation. Second, for each worker in the sample, we obtain a score for each skill category by adding all the standardized variables obtained in the first step. Third, for all skill measures to have a zero mean and standard deviation of one, we do one additional standardization of the six skill categories by subtracting their mean and dividing by their standard deviation. The standardization is performed for each country separately.

The second important difference concerns the difference in the actual questions. Many important questions are extremely similar, for example, those related to ICT skills or STEM skills, but there are others with more salient differences. For example, to build marketing and accounting skills, PIAAC includes a question on the frequency of selling products or services, but STEP does not. Our strategy here has been to base our choices on previous literature using the STEP survey to construct skills measures (Di Carlo et al., 2016; Roseth et al., 2016; Lo Bello et al., 2019) or combining both PIAAC and STEP to compare across countries (Lewandowski et al., 2019). The main difference between these previous studies and our paper is that they have focused on a different set of skills, mirroring the measures available in U.S. surveys instead of those available in the OECD PIAAC surveys.[7]

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[6] The only difference is the exclusion of a variable capturing physical skills that Grundke et al. (2017) included in the ICT measure with a negative weight.

[7] They focus on the difference between cognitive and manual skills and between routine and non-routine tasks.

2.2 Digital intensity

In our econometric analysis, we also estimate differential returns, according to the digital intensity of each economic sector. Digital intensity refers to the degree in which the production and the performance of a given sector has been impacted by the digital transformation, i.e., the same set of technological innovations that have made relevant the skills that are the object of this study. The process of digital transformation is complex, involving more than a mere investment in computers, software, cold computing, or other digital tools, but also "embedding them in production with the appropriate human capital and using them when dealing with clients and suppliers" (Calvino et al., 2018). Looking at digital intensity is important in our context because the skills most relevant to the digital economy may be complementary to the technologies and business practices used by firms. While we do not have data granular enough to explore firms' characteristics, we can, at least, study the heterogeneity on returns by the degree of digital intensity at the sector level.

We proceed by defining an indicator variable of digital intensity for each of 36 economic sectors following the classification established by Calvino et al. (2018) for a subset of OECD countries. Using data from the Latin American region to define the digital intensive indicator variable would be better but lack of data prevents us to do that. Calvino et al. (2018)'s classification employs seven variables to describe a given sector as more or less digital-intensive: level of investment in ICT equipment, level of investment in software and databases, purchases of ICT services, purchases of ICT goods, robot use, revenues from online sales, and intensity of ICT specialists. None of these variables are reliably collected for Latin American and the Caribbean (LAC) countries, so we use the same indicator defined by Calvino et al. (2018) but apply it to our LAC countries.

To determine the extent to which transferring the OECD classifications to LAC countries represents a credible way to proceed, we use the only variable with some correlation to digital intensity available on the LAC region. The International Federation of Robotics (IFR) provides counts of the stock of robots by economic sector, country, and year worldwide, including the four countries under investigation here. We calculate the average number of robots in each economic sector for the entire region, taking the median value across sectors and classifying as "digital intensive" those sectors above the median. We compare this classification specification from the Latin American region to the one appearing in Calvino et al. (2018) to evaluate the viability of the

robot use component of their digital intensive indicator. The comparison indicates a correlation of 0.8 between the Latin American classification and the OECD classification, lending some weight to the use of the OECD classification in our estimates. Still, some important differences exist in the *intensity* of robot use between regions. Table A2 in Appendix A shows the average number of operational robots for seven aggregate economic sectors in the Latin American region, in the United States, and in Western Europe. The number of operational robots is between 4 and 100 times larger in the United States and Europe, relative to Latin America.

In conclusion, the comparison shows that LAC countries and high-income OECD countries are generally similar, in terms of the sectors of the economy with high digital intensity, but that the degree of intensity is likely to be much smaller in LAC countries than in OECD countries.

3 Descriptive Analysis: The Gender Gap

We first describe the gender gaps in the labor market and the gender differentials in the relevant skills variables. In terms of human capital measures, Table 1 documents the high rates of education of the women in our sample, relative to the men: 79% of women are high-educated (upper secondary education completed or more), while the percentage is 71% for men.

In terms of labor market performance, the usual gender gap in earnings emerges: The average wage of low-educated women is 83% of the average wage of low-educated men; for the high-educated group, the value is 87%. We also find the usual gender asymmetries in the distribution of employment, according to sectors and occupations. Services and sales is women's main occupation: 32% of women are employed in this occupational category, relative to 16% of men. Among men, crafts and related trades is the main occupation, employing about 22% of the workforce. In terms of sectors, both women and men are largely employed in the services sector, but the percentage for women is higher, reaching 93%, while, for men, it is 86%. A similar pattern is found when comparing the percentages of women and men employed in digital-intensive sectors. For women, we are looking at 53%, while, for men, it is 50%. The usual gender gap in labor market participation is also confirmed by our data: Figure 1 shows that, on average, 34% of women in the sample do not participate in the labor market, compared to 18% of men. There are

important differences by education levels: Low-educated women participate at a 54% rate, while high-educated women participate at a 73% rate.

Gender differences, with respect to skills relevant to the digital economy, are reported in Figure 2 and at the bottom of Table 1. The largest difference relates to STEM, where the average skill level for men is 0.12 of a standard deviation *above* the mean, while the average for women is 0.15 of a standard deviation *below* the mean.[8] A smaller disadvantage for women is observed in the context of ICT skills, where they hold a value 0.03 of a standard deviation below the mean compared to a similar value ,which is, of course, above the mean for men. On all the other three skills, men and women do not show noticeable differences.

4 Econometric Analysis: Returns to Skills by Gender

This section presents estimates of the impact of skills on hourly wages, according to gender. We also analyze how these returns to skills interact with the digital intensity of the sector in which the worker is employed. The interaction is relevant to understand how skills play a role in the process of matching worker' skills with firms' technology. It also considers that while the digital economy is expanding, it may have not yet reached all the sectors of the labor market.

The econometric analysis focuses on estimating equations of the form:

$$lnw_{ij} = x_{ij}'\beta^g + \alpha^g s_{ij} + \gamma_j^g + \varepsilon_{ij} \qquad (1)$$

where the natural log of the hourly wage of individual i of gender g in country j (w_{ij}) is regressed on a set of individual-level controls (the vector x_{ij}), a measure of the individual skill relevant in the digital economy (s_{ij}) and a country-fixed effect (γ_j). The coefficient of interest is α, representing the percentage change in earnings associated with a unit increase in the amount of skill s. Following the literature estimating earnings functions, we label this coefficient the *return to skills*.

[8] All the skill indexes are normalized to be mean zero and a standard deviation of one in the overall population.

It is worth noting here that the parameters to be estimated are denoted by the superscript g, to indicate that we are estimating gender-specific coefficients. In other words, we are estimating equation (1) separately by gender.[9]

This specification is different, with respect to the one used by OECD (2018a), which performs a similar analysis on OECD countries. OECD's study estimates gender-specific returns to skills by interacting a gender dummy with the skill variable and then estimating on the pooled sample of men and women. In terms of equation (1), this is equivalent to having the superscript g, but only on the α coefficient. We prefer to let the estimator be flexible enough to capture gender-specific returns on all the variables. Without this flexibility, the returns to skills could capture some of the gender-specific impacts of the other covariates. We find that this specification is, indeed, relevant; numerous coefficients are significantly different between men and women. In Section 4.4, we show the extent to which using the OECD (2018a) specifications instead impacts our results.

The individual-level controls included in the vector x_{ij} are quite parsimonious, due partly to data availability and also to the returns we aim to identify. Specifically, the vector includes a constant, age and age squared, an indicator variable of completed upper secondary education or more, and literacy and numeracy test scores.[10] In short, the baseline specification controls for broad human capital indicators (age and education), for a proxy of basic cognitive abilities (literacy and numeracy scores) and for aggregate differences between the economies (the country-fixed effects). The only additional controls available across all data sets, available for our inclusion in the specification, are sectors and occupations indicator variables. We decided not to include them in the baseline specification for the following reason: Choice of sector and occupation is endogenous and, as such, the overall returns to skills may legitimately include the return to the choice of a certain occupation/industry cell. Since we are interested in gender gaps in the overall return to skills, we have preferred not to decompose the returns in the component due to occupation and sector choices and in the component due to differences within a given sector and occupation cell.

[9] To simplify notation, we do not add the indicator g to the observed variables, but it is understood that we will include in each regression only individuals belonging of a specific gender.

[10] Literacy and numeracy test scores are, unfortunately, not available for all countries. Literacy scores are available for Bolivia, Colombia, and Chile, while numeracy scores are only available for Chile. We have therefore decided to have them interact with the country's fixed effects in the section for specification, pooling all the countries together.

Still, estimating the coefficient conditional on industry and occupation is informative, and we present these estimates in Section 4.4.

4.1 Main Results

The main results on returns to skills are presented in Figure 3. The two main cognitive skills relevant in the digital economy – ICT and STEM – show positive and significant returns for both men and women, but, in STEM, the returns are significantly higher for men.[11] Specifically, a one standard deviation increase in the STEM skill measure implies a 15.1% increase in wages for men and an 8.7% increase in wages for women. ICT skill returns are more similar across genders, ranging from 16.9% for women to 17.6% for men. The returns to the other skills are lower but still positive and significant except for marketing and accounting for women.

Compared with the returns estimated in OECD countries, the returns to ICT and STEM are higher than the estimated average over the pooled set of 31 OECD countries. OECD (2018a) estimates returns to ICT skills to be about 12% for women and about 10.5% for men. The returns to STEM skills are estimated at 4% and 4.5%, for women and men, respectively. Contrary to the results for the four LAC countries, there is a gender gap in returns to ICT, favoring women, while there is no significant difference in returns to STEM by gender.[12]

We have tried to determine whether the difference in results, with respect to OECD (2018a), derives from differences in the specification. As mentioned above, even when the variables employed are comparable, the specifications are slightly different: OECD (2018a) estimates that by having a gender dummy interacted with skills, while we prefer a more flexible specification, where all the returns are allowed to be gender-specific. We have run the specification preferred by OECD (2018a) on our data and found that the difference in specification explain only a small portion of the difference. We discuss the results in Section 4.4.

The main results of the returns to skills interacted with the level of digital intensity in the sector are presented in Figure 4. The figure reports the additional impact of a given skill when the worker

[11] We report point estimates with the dot and the diamond, and the 90% confidence interval with vertical lines. As a result, any time that the vertical line does not cross zero, it means that the coefficient is significantly different from zero.

[12] See Figure 1.7, page 16, OECD (2018a).

is employed in a sector with high digital intensity. The exercise is meant to capture the extent to which a portion of the overall returns discussed above is due to composition effects across sectors, i.e., if the skills have significant and positive returns only in those sectors that are more impacted by the digital economy, or if they are equally valuable across all sectors. The figure shows that digital intensity does not generally have a significant impact: Most of the coefficients are not significantly different from zero, and the point estimates are very close to zero.[13] Again, this result stands in stark contrast with the findings for OECD countries. OECD (2018a) estimates that working in digital-intensive industries increases returns to skill by about 2 to 3 percentage points.[14] The results for our four Latin American countries indicate that either digital intensity is not very pronounced in Latin America or that the skills under consideration are valuable across all the sectors of Latin American economies. Even with the data at our disposal, we cannot disentangle the two explanations, but some of the evidence discussed in Section 2.2 indicate that digital intensity is, indeed, less pronounced in Latin America than in OECD countries. Specifically, Table A2 in Appendix A shows that the average number of operational robots for seven aggregate economic sectors (the only direct measure of digital intensity available for LAC countries) is between 4 and 100 times larger in the United States and Western Europe than in Latin America. This result is consistent with the analysis based on the broader Digital Adoption Index, reported by Busso et al. (2017). The index shows that Latin America lags behind high-income economies in terms of availability and adoption of digital technologies.[15] In other words, if the sectors of the economy with high digital intensity are similar between LAC countries and high-income OECD countries, the extent of the intensity is much smaller in LAC.

To summarize the results obtained by aggregating the data gleaned from the four countries under study, (i) we estimated significant and large returns to ICT and STEM, with no significant gender differences on the first, but a significant gender gap in favor of men on the second. (ii) For the other skill measures, we found positive but lower returns with mainly not statistically significant differences between women and men. (iii) The digital intensity of the sectors does not seem a crucial factor in determining these returns.

[13] The exception are self-organization and marketing & accounting, which have, respectively, slightly smaller and slightly higher returns when used in digital-intensive sectors.
[14] See Figure 1.3, page 12, OECD (2018a).
[15] See Figure 4.8, page 95, Busso et al. (2017).

In Appendix C, we look at each country in isolation from the others; we actually found results for each that are qualitatively similar to the aggregate for Chile, Bolivia, and Colombia but with some differences in magnitude. Returns to STEM are higher than the aggregate of Chile and lower than the aggregate of Bolivia and Colombia. El Salvador, on the other hand, does not report a gender gap favoring men in returns to STEM; both men and women have positive but similar returns. Returns to ICT in El Salvador are also a little different than the aggregate, indicating a higher (but not significantly so) return for women. Extra returns for working in digital-intensive sectors estimated by country confirm the aggregate results: Digital intensity does not significantly increase returns to skills.

4.2 Heterogeneous Effects

We focus on the heterogeneous effect on the individual characteristic most relevant with respect to skills formation and acquisition: schooling levels. We focus on upper secondary education, and we report the differential effect on the returns of individuals who completed this educational level with respect to individuals who completed less. The results are reported in Figure 5. They show that higher levels of education yield significantly higher returns for men but not for women. For women, the increase in returns never departs significantly from zero, and the point estimates are always lower than those for men. In the next section, we discuss whether these differences may be due to the different selection in the labor market by gender.

These results are more mixed when looking at regressions by country (Figure C4 in Appendix C). In Chile, we estimate significantly higher returns for high-educated men on all skills except readiness to learn. In Bolivia and El Salvador, only half of the skill types demonstrate significant increases; in Colombia, only one. What remains broadly similar to the aggregate results is that the increase in returns is higher for men than women. The only important exception is Colombia, where the point estimate of increase in ICT and STEM is higher for women. However, the estimated coefficient is not significantly different from zero in either case.

4.3 Selection in the Labor Market

Women participate in the labor market less than men. This is a common feature among most labor markets, and it holds in our samples. Figure 1 shows that women participate in the labor market less than men at all education levels. The Web Appendix shows the results of each country. Because participation is non-random – i.e., it is the result of a choice – the women we observe working may be systematically different from those not working. If the characteristics over which they are different are related to their performance in the labor market, then the return to skills we estimated are only representative of the population of women working and not of the entire population of women. This bias may affect some relevant policy implications. For example, if a policy is successful in increasing the skill levels of women, should we expect the women's returns that were affected by the policy to be more like those of the women currently participating or the ones who are not? Because some of the factors related to productivity remain unobserved, it is not easy to answer this question. It may therefore be useful to estimate a set of returns that can indicate if the estimated returns of women currently working are significantly different from those of the overall population of women.[16]

We adopt a standard Heckman selection model (Heckman, 1979) to obtain returns that consider selection in the labor market. To avoid relaying only on distributional assumptions for identification, we adopt an exclusion-restriction: We assume that each woman's number of children affects her participation decision but not the wage paid to her.[17]

Results are presented in Figure 6 and show relatively small changes with respect to the baseline specifications reported in Figures 3 and 5. Still, two small differences are worth mentioning. First, the point estimate of the return to ICT becomes higher for women than men. However, both in the baseline specification and in the selection-correction specification, the differences in returns between men and women are not significantly different from each other. Second, the gap in favor

[16] Notice that in principle, the same selection problem also applies to men but because a high proportion of men participate in the labor market, we follow the common practice of ignoring selection in the labor market for them. In other words, even if not all men participate in the labor market, the small proportion of men who do not is unlikely to affect the overall estimates very much.

[17] This assumption is common in the literature, but it is not without limitations. If it is true that firms cannot offer wage contracts contingent to the presence of children, some evidence shows that the unequal distribution of household work between men and women may generate a systematic (and potentially causal) association between wages and the presence of children.

of men in returns to STEM is reduced because the point estimate for women increases from 8.7% to 9.5%.

By looking at results by country (reported in Figure C5 of Appendix C), we can see that these minor changes are mainly driven by Chile. In Chile, controlling for selection increases women's returns to ICT from 18.9% to 24.0% and returns to STEM from 11.0% to 18.3%. Another relevant change takes place in Bolivia, where women's returns to STEM become significantly different from zero when controlling for selection.

With respect to heterogeneous returns, correcting for selection does not qualitatively change the results. The results are reported in Figure 7 and should be compared to Figures 4 and 5. Overall, they confirm the lack of significantly higher returns for agents working in the digital-intensive sector and reiterate that only men have significantly higher returns when they complete upper secondary education.

Finally, estimates obtained by correcting for selection show that this is not the source of differences with respect to returns estimated in OECD countries (OECD 2018a). Selection-correction slightly increases the differences because it leads to slightly higher returns to ICT and STEM for women.

4.4 Robustness Analysis

In this section, we provide a robustness analysis along three dimensions. First, we study how the results change when we replicate the specifications of the OECD (2018a); we constrain all the coefficients to be the same for men and women except for the returns to skills. Second, we study how the results change when we control for sectors and occupations. Finally, we check if the results controlling for selection are affected by using different exclusion-restrictions in the selection model.

Results constraining all the coefficients to be the same for men and women except for the returns to skills are reported in Table B7. This specification consists in running equation (1) on a sample pooling together men and women and then interacting the women indicator variable with the variable measuring the specific skill under consideration. Our favorite baseline specification allows all the coefficients to be gender-specific because it allows for more flexibility. This different constrained version lets only the return to skill be gender-specific; as a result, returns to skills may

capture some of the gender-specific impacts of the other covariates. By focusing on the two skills with the strongest impact in the baseline specification (ICT and STEM), the estimation results in the constrained specification are essentially identical to ICT and show a small difference to STEM. If, in the baseline specification, men's returns to STEM are estimated to be 15.2%, those for women are 6.7 percentage points lower. Men's returns on the constrained specification are estimated to be 14.9%, whereas those for women are 5.9 percentage points lower. This slightly lower gender gap in constrained specification is an indication that allowing for gender-specific returns on the other covariates and on country-fixed effects is useful for estimating returns closer to consistent values.

Results controlling for sectors and occupations are reported in Table B8. As mentioned, sectors and occupations are important controls given that each sector/occupation cell may require and use the skills in the digital economy differently. Conditioning on them may clarify if the differences in returns we observed are due to the sorting of men and women over these cells or to different returns within cells. Because occupational choices are endogenous and within-sector differences may be affected by unobservable characteristics, this analysis remains largely descriptive. In other words, the overall returns to skills may legitimately include the return to the choice of a certain occupation. The estimation results conditioning on sectors and occupation qualitatively confirm the main result in the baseline specification: We estimate significant returns to ICT and STEM, with no significant gender differences in the former but a significant gender gap in favor of men in the latter. Quantitatively, both ICT and STEM returns are estimated to be lower when sectors and occupation controls are introduced. For example, women's ICT returns decreased from 16.8% in the baseline specification to 7.0% in the specification controlling for sector and occupation; the corresponding values for men were 17.4% and 7.1%, respectively. These results indicate, probably not surprisingly, that a portion of the returns to ICT and STEM is because individuals who possess those skills work in a sector and occupation that pay relatively more in comparison to people with a lower level of these skills. More interestingly, the gender gap in ICT returns is unaffected when we change the specification, unlike the gender gap in STEM returns. In other words, conditioning on the sector and occupation cell, men's returns to STEM are estimated to be much greater than women's returns to STEM than in the economy as a whole. The results suggest that different choices of occupation and sector are not the main driver of the overall gender gap in STEM returns;

women's occupational choices, vis-a-vis men's, decrease the gender gap in returns present within sector/occupation cells.

Results controlling for how different exclusion-restrictions affect our selection model are reported in Table B9. In our baseline selection model, we used the presence of children as the exclusion-restriction, a variable very likely to affect the participation decisions of women. However, not only fertility decisions are endogenous, but the presence of children may also directly impact wages and not only participation. Still, we are limited in terms of data availability on the exclusion-restrictions we can use in the selection model. Furthermore, the number of children is the only variable available on all data sets. However, if we limit ourselves to the STEP countries, we can use additional information. Specifically, we use information about whether the mother or father of the person answering the survey lives in the household. This presence may be very influential on the labor market participation decision of women, either because they can help in household production or because they need resources for their care. We therefore built an indicator variable for whether the mother or father of the person answering the survey is living in the household. We use it as an exclusion-restriction alone and jointly with the presence-of-children variable. Estimation results show very little sensitivity to the various exclusion-restrictions. For example, the overall STEM return in STEP countries is estimated to be about 5.7% without controlling for selection. When controlling for selection, it is estimated to be just a little lower, ranging from 5.13% when using only the presence of children as an exclusion-restriction, to 5.17% when using only the presence of grandparents, to 5.16% when using both.[18]

5 Post-Estimation Analysis: Decomposing the Gender Gap

The previous section presented estimates of the returns to skills and to other individual characteristics by gender. Using these estimates, it is possible to decompose the overall gender gap

[18] We have also run OLS regressions using the exclusion-restriction variables directly in the wage regressions. We found that they are typically not significant, while they always are in the participation-decision equation. Although the exclusion-restrictions are not formally testable since we use them for identification, this reduced form results lends some credibility to them.

in the portion due to differences in returns and to differences in endowments. The most popular procedure to accomplish this is labeled in the literature as Oaxaca-Blinder decomposition.[19] It is simply an accounting exercise based on mean differences. The regressions we have presented in the previous sections and defined in equation (1) are ordinary least squares (OLS) regressions guaranteeing that:

$$\overline{lnw_g} = \overline{x_g}'\hat{\beta}^g + \hat{\alpha}^g\overline{s_g} + \bar{\hat{\gamma}}^g \qquad (2)$$

where the overbar denotes sample mean, the hat denotes estimated value, and the indicator *g=m,w* denotes gender-specific values. The country-fixed effect component is averaged out over all the individuals living in the country.[20] In other words, equation (2) states that OLS estimation guarantees that the mean of the dependent variable is exactly predicted by the estimated coefficients applied to the sample mean of the regressors. Based on this result and one step of algebra, the gender earnings gap – the difference in average earnings between men and women – can be decomposed in the portion due to differences in the sample mean of the regressors (the *endowments*) and in the portion due to differences in the estimated coefficients (the *returns*). Focusing on the returns and endowments of relevant skills related to the digital economy – denoted with *s* – we can write:

$$\overline{lnw_m} - \overline{lnw_w} = \hat{\alpha}^m(\bar{s}_m - \bar{s}_w) + (\hat{\alpha}^m - \hat{\alpha}^w)\bar{s}_w + (\bar{x}_m{}'\hat{\beta}^m - \bar{x}_w{}'\hat{\beta}^w) + (\bar{\hat{\gamma}}^m - \bar{\hat{\gamma}}^w) \qquad (3)$$

[19] See Blinder (1973) and Oaxaca (1973). For a more recent assessment of the approach, see Oaxaca and Ransom (1994). For a more general decomposition involving the entire distribution, see Machado and Mata (2005).

[20] To formally define it, we need to add an indicator function $d_i(j)=1$ if individual i lives in country j, leading to:

$$\bar{\hat{\gamma}}^g = \sum_{j=1}^{J}\sum_{i=1}^{N} d_i(j)\hat{\gamma}_j^g$$

where the first term on the right-hand side denotes gender differences in endowments in digital-economy-relevant skills (weighted by the male return $\hat{\alpha}^m$) and the second term denotes gender differences in returns to those skills (weighted by the female endowment $\bar{s}_w$).

Figure 8 reports the ratio between each of these two terms and the overall gender gap. For example, looking at STEM skills, we estimate that both gender differences in endowments and in returns have a significant impact in explaining the gender gap. The point estimates indicate that endowments could be responsible for up to 30% of the difference and returns for up to 80%.[21] We see this as the main result to be drawn from the decomposition. Two other significant effects are present: Differences in ICT endowments have a marginally significant impact, whereas differences in returns in marketing and accounting have a more substantial impact, with the potential to explain up to 65% of the gap. We perform an additional exercise by reporting the endowment and returns components when including all skills measures at the same time. Results appear in the last panel of Figure 8 and show that endowments explain approximately 40% of the gender wage gap, while the returns to skills do not have any explanatory power.

Results by country are reported in Appendix C, Figure C7. They confirm the overall main results for Bolivia, Chile, and Colombia: STEM has a significant impact, with differences in returns contributing up to 64% of the gap in Bolivia, up to 28% in Chile, and up to 90% in Colombia. El Salvador is the only country where STEM does not have either an economically significant or a statistically significant impact on the earnings gender gap. In terms of other skills, the country-by--country results show that the significant impact of marketing and accounting in the aggregate sample was mainly driven by Colombia.

6 Conclusion

We studied gender differentials in the labor market with a focus on skills relevant to the digital economy. Specifically, we estimated the returns to skills using standard wage regressions, but we allowed for heterogeneous effects and considered selection in the labor market. We focused on

[21] Recall that the estimated returns are based on running separate regressions, each with only one of the digital-economy-relevant skills at the time. Since there are likely to be correlations between skills, the estimates report the maximum impact that the skill may have in explaining the gap.

four Latin American countries for which all the relevant data are available: Bolivia, Chile, Colombia, and El Salvador.

We found that the group of skills described as ICT and as STEM have significant positive returns for both men and women. However, there is a significant gender gap in favor of men on the returns to STEM, while the returns to ICT are very similar between the two genders. We also estimated the returns in specifications allowing for heterogeneity by education and sector of occupation. We found that having upper secondary education or higher implies significantly higher returns for men but not for women. Unlike the results obtained on OECD countries (OECD, 2018a; OECD, 2018b), we did not find any significant impact related to working in a digital-intensive sector. This means that either digital intensity is less pronounced in Latin American countries than OECD countries or that the skills under consideration are valuable across all sectors of Latin American economies. All these results are confirmed when controlling for selection in the labor market for women. We also performed a robustness analysis where we studied how results change by varying the specification and by employing various exclusion-restrictions in the selection model.

Finally, we provided a decomposition of how skills relevant to the digital economy may contribute to the gender gap in wages. By computing a standard Oaxaca-Blinder decomposition based on our estimates, we concluded that both gender differences in endowments and in returns to STEM skills have a significant impact in explaining the gender gap in earnings. The point estimates indicate that endowments could be responsible for up to 30% of the difference and returns for up to 80%.

The summary of results provided so far is aggregated over the four countries under consideration. Many of our results were confirmed when performing the same analysis for each country separately. The most relevant differences between countries concerned returns to STEM. They were estimated to be higher than the aggregate in Chile and lower than the aggregate in Bolivia and Colombia. El Salvador is the only country not reporting a gender gap in favor of men in returns to STEM. As a result, El Salvador is the only country for which gender differences related to STEM skills do not explain the overall gender gap in earnings.

Why returns to STEM exhibit such strong gender asymmetries can only be partially answered by our analysis. The list of possible explanations is broad. The first possibility is selection into different sectors and occupations; men and women may systematically choose to work in different jobs, even when possessing similar skills. Our robustness analysis controlling for sectors and

occupations indicated that this is not the case: The within-sector and occupation gaps are higher than the overall gap. The second possibility is selection in the labor market, i.e., women participate in the labor market at a lower proportion than men. If only the relatively less productive women participate, then their lower returns may reflect a genuine productivity differential. Our analysis estimating a series of selection models indicated that this mechanism may at most explain a very small portion of the differential. The third possibility is different labor market experiences and labor market attachments. Some evidence suggests that time investments in household production are very different between men and women.[22] This is reflected both in the extensive and intensive margins of labor supply. The extensive margin differential is reflected in the lower participation rate for women, and the selection models we estimated take this into account. The intensive margin is reflected in hours worked, which is accounted for by using hourly wages as dependent variables in our estimations. However, there is an important dynamic element that our static estimates could not properly consider; over time, a lower labor supply implies lower accumulation of human capital on the job. Our controls for labor market experience is very crude, and therefore, some of the impact of human capital accumulation on the job may be picked up by other returns, such as returns to education and returns to skills. The only objection to this explanation is that human capital accumulation on the job should involve all skills, not only STEM skills, while we estimate the gender gap only on STEM returns. The fourth possibility is discrimination against women in STEM professions. There is a growing, even if by no means conclusive, literature suggesting that STEM and related professions may be more prone to gender discrimination than other professions.[23] With the data at our disposal, we neither can exclude nor confirm such an explanation. Finally, the fifth possibility is that the quality of the STEM skills acquired by men and women may be different, explaining the gap in terms of underlining productivity differentials. This may result from human capital acquired before entering the labor market. By controlling for numeracy score, our regressions should condition on some of those differences, but the difference may result also from human capital acquired on the job after entering the labor market. This is the same mechanism we described when discussing the dynamic implication of gender differences in

[22] Evidence collected in time-use survey provides convincing evidence in this respect. For cross-country evidence, see van der Lippe et al. (2011) and Apps and Rees (2005). For evidence on a Latin American country, see Salazar-Saenz (2019) on Colombia.
[23] See, for example, Buffington et al. (2016) and Carrell et al. (2010).

labor supply. Given the limited controls for dynamic behavior in our empirical models, this is another mechanism that cannot be ruled out.

In conclusion, we found that if investing in skills relevant to the digital economy, specifically in ICT and STEM, may be beneficial for the labor market performance of both men and women, it remains a relevant open question in understanding why returns to STEM exhibit such a strong gender gap. Our results can rule out some explanations but cannot precisely point to the actual mechanism. At least two explanations remain good candidates to explain the gender gap in STEM returns: the presence of stronger discrimination against women in STEM-related professions than in other professions and the life-cycle impact of a different rate of human capital accumulation on the job between men and women. The first suggests policies directly targeting the labor market, and the second suggests policies improving work-life balance for both men and women.[24]

[24] For a recent assessment of these policies in the U.S., see Doran et al. (2018).

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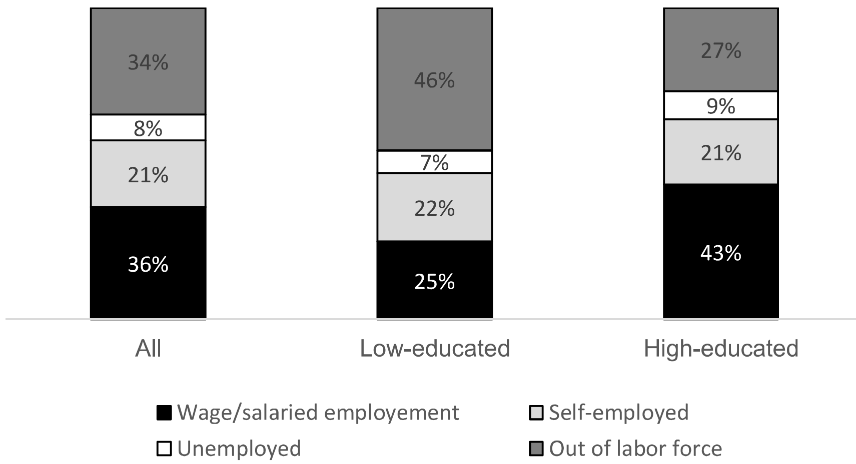
Table 1: Descriptive Statistics

	All workers			Women			Men		
	All	Low-educated	High-educated	All	Low-educated	High-educated	All	Low-educated	High-educated
Share of women	0.44	0.36	0.47						
	(0.5)	(0.48)	(0.5)						
Age	34.96	37.26	34.17	34.67	37.05	34.05	35.18	37.39	34.28
	(11.79)	(13.43)	(11.08)	(11.45)	(13.04)	(10.92)	(12.05)	(13.65)	(11.22)
Share of low-educated	0.25			0.21			0.29		
	(0.43)			(0.41)			(0.45)		
Share of high-educated	0.75			0.79			0.71		
	(0.43)			(0.41)			(0.45)		
Literacy score	0.79	0.76	0.80	0.79	0.74	0.80	0.79	0.77	0.79
	(0.26)	(0.28)	(0.25)	(0.26)	(0.29)	(0.25)	(0.26)	(0.27)	(0.26)
Hourly wage in dollars at PPP of 2005	4.55	3.02	5.07	4.28	2.68	4.70	4.76	3.21	5.39
	(4.72)	(3.34)	(5)	(4.59)	(3.27)	(4.79)	(4.81)	(3.37)	(5.16)
Distribution of employment by occupation									
Managers	0.02	0.00	0.03	0.02	0.01	0.02	0.03	0.00	0.04
	(0.16)	(0.05)	(0.18)	(0.14)	(0.08)	(0.16)	(0.17)	(0)	(0.2)
Professionals	0.10	0.01	0.13	0.12	0.02	0.15	0.08	0.00	0.11
	(0.3)	(0.09)	(0.33)	(0.33)	(0.13)	(0.36)	(0.27)	(0.06)	(0.31)
Technicians and associate professionals	0.12	0.03	0.16	0.13	0.01	0.17	0.11	0.04	0.15
	(0.33)	(0.17)	(0.36)	(0.34)	(0.1)	(0.37)	(0.32)	(0.19)	(0.35)
Clerical support workers	0.14	0.05	0.17	0.16	0.06	0.19	0.12	0.05	0.15
	(0.35)	(0.22)	(0.38)	(0.37)	(0.23)	(0.39)	(0.33)	(0.21)	(0.36)
Services and sales workers	0.23	0.24	0.23	0.32	0.39	0.30	0.16	0.16	0.16
	(0.42)	(0.43)	(0.42)	(0.47)	(0.49)	(0.46)	(0.37)	(0.36)	(0.37)
Craft and related trades workers	0.14	0.24	0.10	0.04	0.09	0.03	0.22	0.33	0.17
	(0.34)	(0.43)	(0.3)	(0.2)	(0.28)	(0.16)	(0.41)	(0.47)	(0.38)
Plant and machine operators and assemblers	0.10	0.16	0.08	0.05	0.10	0.04	0.14	0.19	0.12
	(0.3)	(0.37)	(0.28)	(0.22)	(0.31)	(0.19)	(0.35)	(0.4)	(0.33)
Elementary occupations	0.14	0.27	0.10	0.15	0.33	0.10	0.14	0.23	0.10
	(0.35)	(0.44)	(0.3)	(0.35)	(0.47)	(0.3)	(0.34)	(0.42)	(0.29)
Distribution of employment by economic sector									
Manufactures	0.11	0.12	0.11	0.07	0.09	0.07	0.14	0.13	0.15
	(0.32)	(0.32)	(0.31)	(0.26)	(0.28)	(0.26)	(0.35)	(0.34)	(0.35)
Services	0.89	0.88	0.89	0.93	0.91	0.93	0.86	0.87	0.85
	(0.32)	(0.32)	(0.31)	(0.26)	(0.28)	(0.26)	(0.35)	(0.34)	(0.35)
Digital intensive industries	0.51	0.39	0.55	0.53	0.47	0.54	0.50	0.34	0.56
	(0.5)	(0.49)	(0.5)	(0.5)	(0.5)	(0.5)	(0.5)	(0.48)	(0.5)
Skill measures									
ICT skills	0.00	-0.57	0.20	-0.03	-0.70	0.14	0.03	-0.49	0.24
	(1)	(0.79)	(0.99)	(0.99)	(0.73)	(0.98)	(1)	(0.81)	(0.99)
Readiness to learn	0.00	-0.32	0.11	0.01	-0.34	0.10	-0.01	-0.31	0.11
	(1)	(1.08)	(0.95)	(0.97)	(1.01)	(0.93)	(1.03)	(1.12)	(0.96)
Management and communication	0.00	-0.48	0.17	-0.01	-0.58	0.14	0.01	-0.42	0.19
	(1)	(0.9)	(0.98)	(0.99)	(0.89)	(0.96)	(1.01)	(0.9)	(1)
Self-organization	0.00	-0.16	0.06	-0.03	-0.18	0.01	0.02	-0.15	0.09
	(1)	(1.07)	(0.96)	(1.02)	(1.07)	(1)	(0.98)	(1.07)	(0.93)
Marketing and accounting	0.00	-0.26	0.09	0.08	-0.22	0.15	-0.06	-0.28	0.03
	(1)	(1)	(0.99)	(1)	(1.04)	(0.98)	(1)	(0.97)	(0.99)
STEM-quantitative skills	0.00	-0.38	0.13	-0.15	-0.62	-0.02	0.12	-0.24	0.27
	(1)	(0.76)	(1.04)	(0.92)	(0.6)	(0.95)	(1.04)	(0.8)	(1.09)
Observations	3,242	820	2,422	1,434	298	1,136	1,808	522	1,286

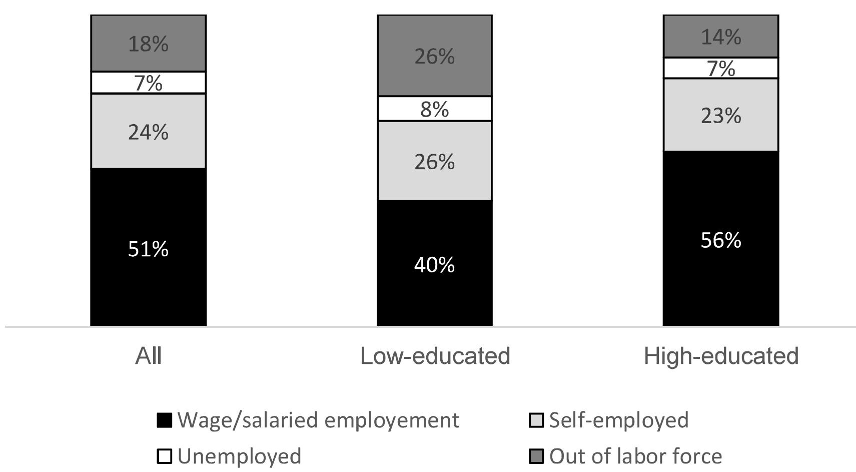
Notes: Table reports descriptive statistics on the estimation sample extracted from the 2014 PIAAC (Chile) and 2012 (Bolivia, Colombia) and 2013 (El Salvador) STEP survey. Standard deviation is in parentheses. Low-educated: Lower secondary education or lower. High-educated: Upper secondary education or above. ICT: Information and communication technologies.

Figure 1: Distribution of Labor Market States

Women



Men

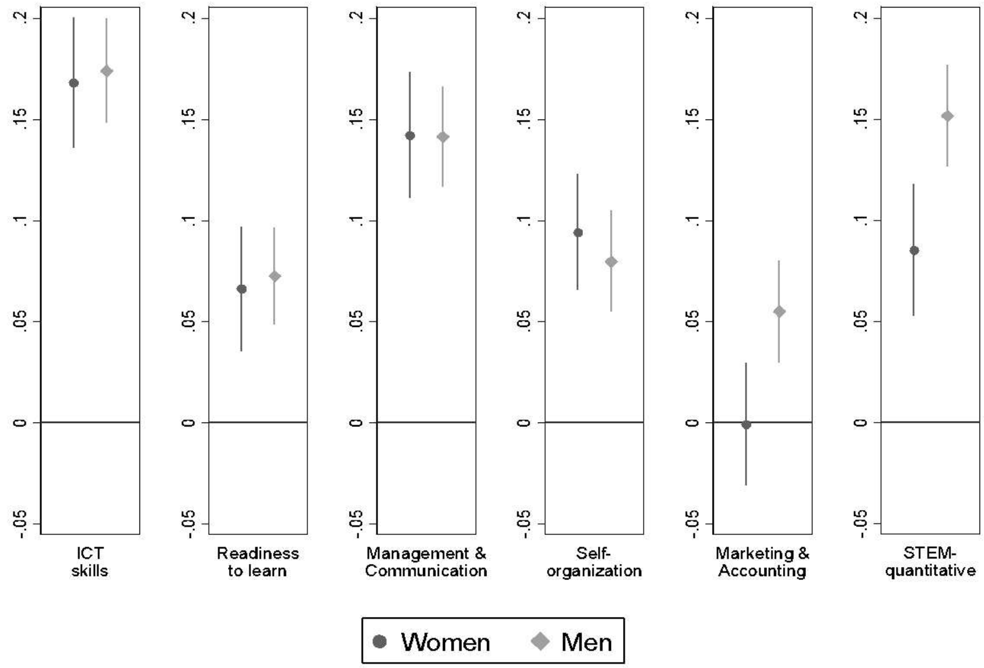


Source: Own elaboration based on PIAAC and STEP surveys.

Figure 2: Skills in the Digital Economy

Source: Own elaboration based on PIAAC and STEP surveys.

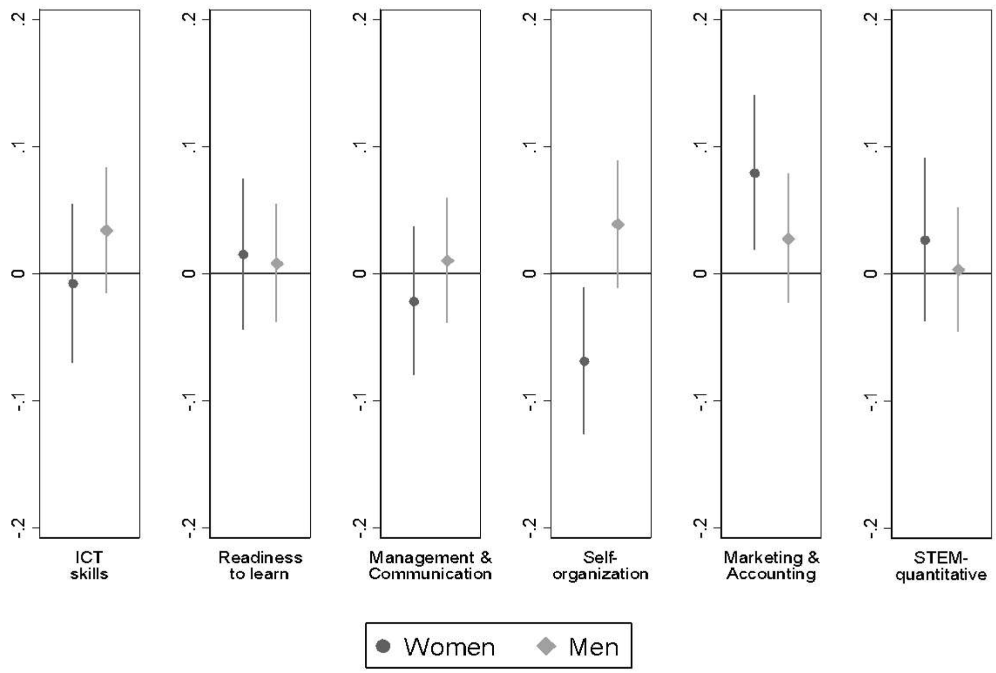
Figure 3: Returns to Skills



Source: Own elaboration based on PIAAC and STEP surveys.
Note: The figure reports the coefficient estimate of those individual skill that are relevant to the digital economy in the log hourly wage regression defined in equation (1). It represents the percentage change in hourly wages of one standard deviation increase in the skill measure. The dot and the diamond are the point estimates, while the vertical lines show the 90% confidence interval of the estimate. The complete specification is defined in Section 4, equation (1). Complete results are available in Table B1 in Appendix B.

Figure 4: Returns to Skills in Sectors with Varying Digital Intensity:

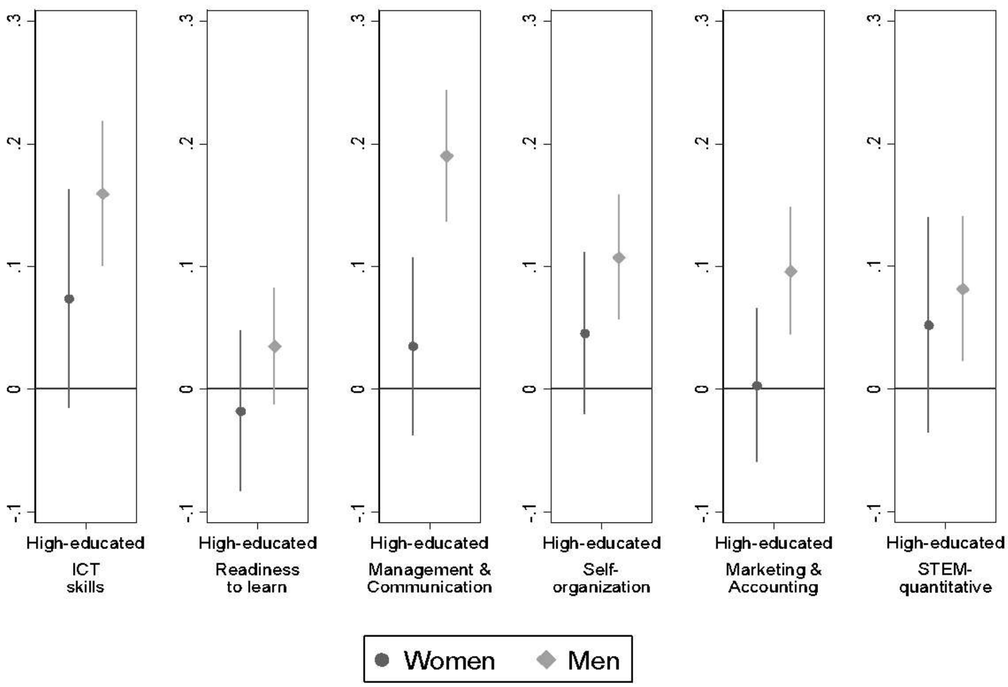
Extra Returns for Working in Digital-Intensive Sectors



Source: Own elaboration based on PIAAC and STEP surveys.
Note: The figure reports the estimate of the coefficient capturing the interaction between the individual skill relevant to the digital economy and a dummy equal to 1 if the sector is a digital-intensive sector. The estimate is obtained in the log hourly wage regression defined in equation (1). It represents the percentage change in hourly wages of a one standard deviation increase in the skill measure of a digital-intensive sector with respect to a nondigital-intensive sector. The dot and the diamond are the point estimates, while the vertical lines show the 90% confidence interval of the estimate. The complete specification is defined in Section 4, equation (1). Complete results are available in Table B2 in Appendix B.

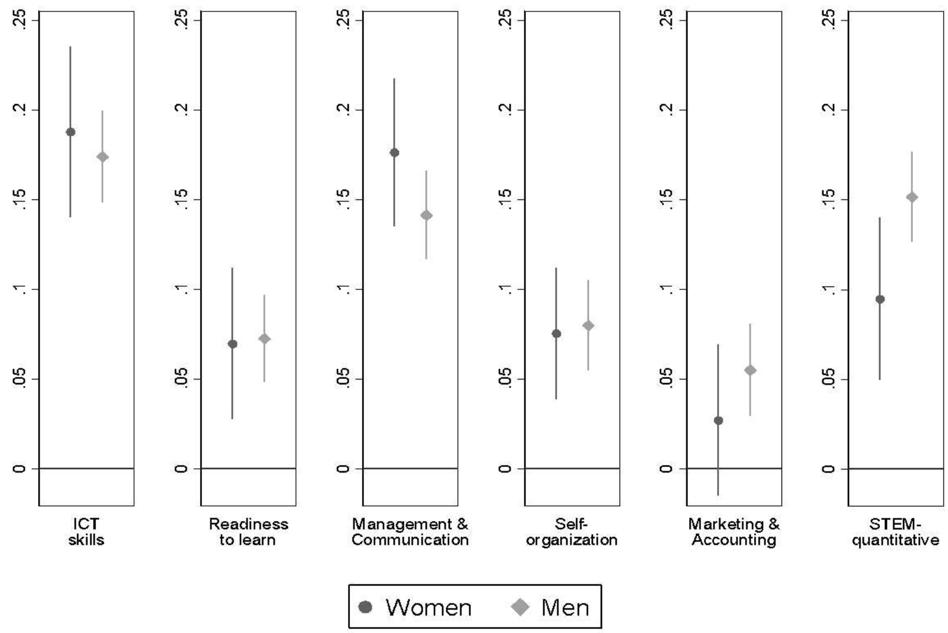
Figure 5: Heterogeneous Effects by Education:

Extra Returns to Skills for High-Educated Workers



Source: Own elaboration based on PIAAC and STEP surveys.
Note: The figure reports the coefficient estimate for the interaction between the individual skill relevant to the digital economy and a dummy equal to 1 if the individual has completed upper secondary education or above. The estimate is obtained in the log hourly wage regression defined in equation (1). It represents the percentage change in hourly wages of a one standard deviation increase in the skill measure for individuals with at least upper secondary education completed with respect to individuals who have not completed that level. The dot and the diamond are the point estimates, while the vertical lines show the 90% confidence interval of the estimate. The complete specification is defined in Section 4, equation (1). Complete results are available in Table B3 in Appendix B.

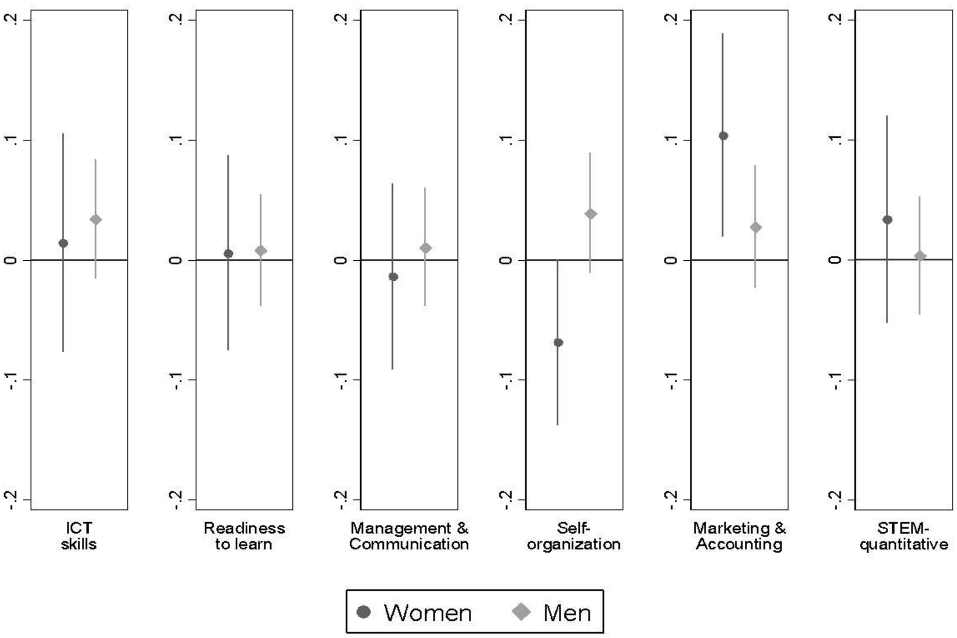
Figure 6: Returns to Skills: Correcting for Selection in the Labor Market



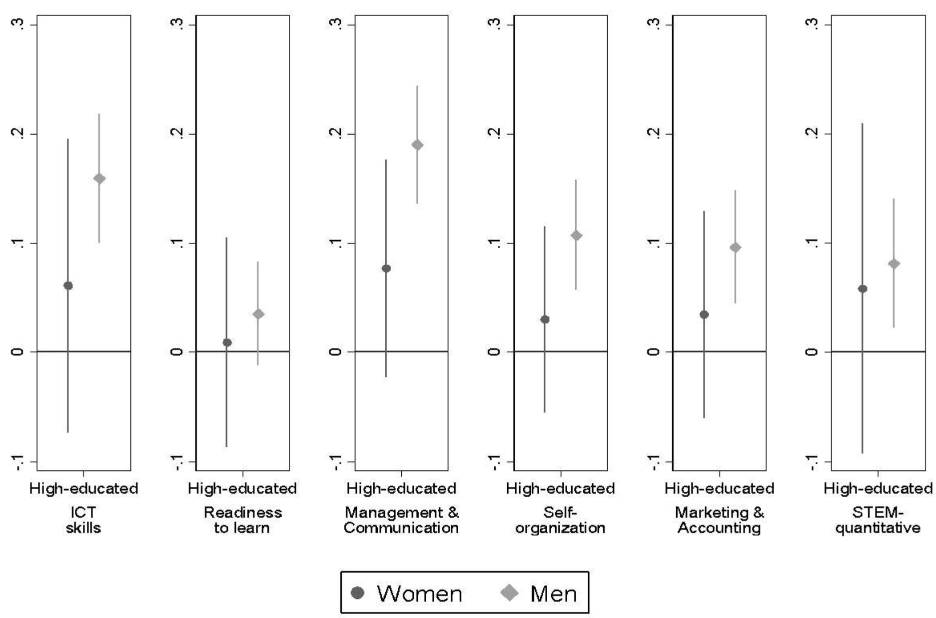
Source: Own elaboration based on PIAAC and STEP surveys.
Note: The figure reports the same estimates as Figure 3 but corrects for selection in the labor market for women. See Section 4.3 for additional details. We correct for selection only on women because men have a sufficiently high participation rate. Complete results are available in Table B4 in Appendix B.

Figure 7: Heterogeneous Returns to Skills: Correcting for Selection in the Labor Market

Extra Returns for Working in Digital-Intensive Sectors



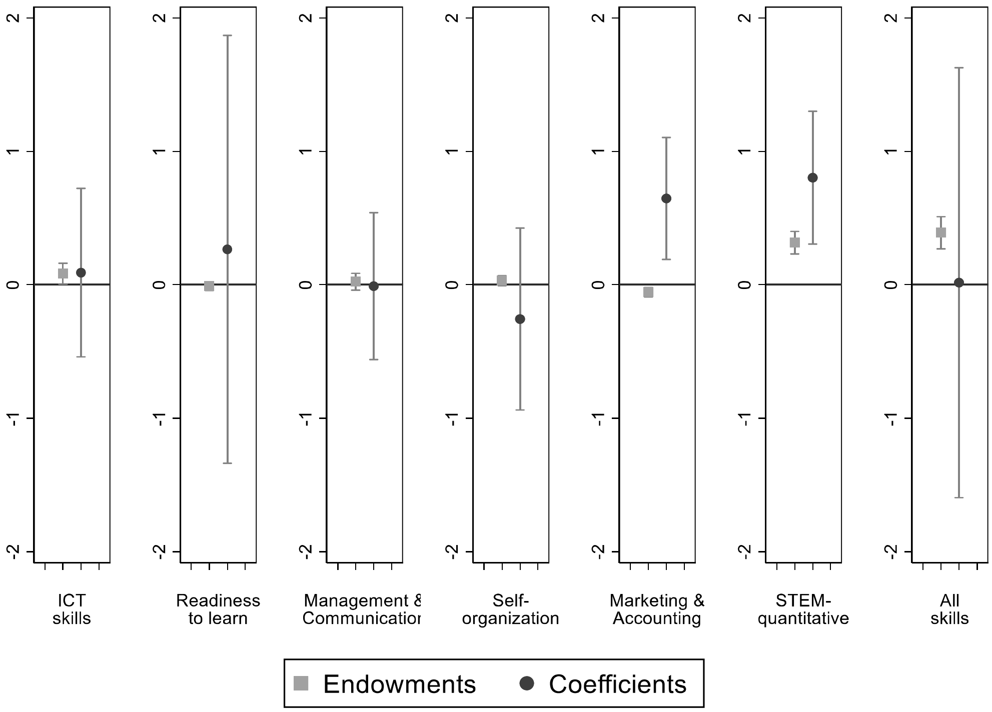
Extra Returns for High-Educated Workers



Source: Own elaboration based on PIAAC and STEP surveys.

Note: The figure reports the same estimates as Figure 4 (top panel) and Figure 5 (bottom panel) but corrects for selection in the labor market for women. See Section 4.3 for additional details. We correct for selection only on women because men have a sufficiently high participation rate. Complete results are available in Tables B5 and B6 in Appendix B.

Figure 8: Contribution of the Skills' Returns and Endowments to the Gender Wage Gap



Source: Own elaboration based on PIAAC and STEP surveys.
Note: The figure reports results based on the Oaxaca-Blinder decomposition defined in equation (3). The *Endowments* correspond to the first term on the right-hand side of equation (3) and represent the contribution to the overall gap due to gender differences in endowments (quantities) of each individual skill relevant to the digital economy. The *Coefficients* correspond to the second term on the right-hand side of equation (3) and represent the contribution to the overall gap due to gender differences in returns (prices) to those skills. The dot and the diamond are the point estimates, while the vertical lines show the 90% confidence interval of the estimate. Complete results are available in Table B10 in Appendix B.

APPENDIX A: Data Appendix

Table A1. Skill-Related Questions from the PIAAC and STEP Surveys

Skill measure	PIAAC		STEP	
	Questions used	Metric	Questions used	Metric
ICT skills	Frequency of spreadsheets use, e.g. Excel	1 (never) to 5 (every day)	Regular use of telephone, mobile phone, pager, or other communication device	Yes/No
	Frequency of programming language use	1 (never) to 5 (every day)	Regular use of barcode reader	Yes/No
	Frequency of transactions through Internet (banking, selling/buying)	1 (never) to 5 (every day)	Use of a computer	Yes/No
	Frequency of email use	1 (never) to 5 (every day)	Frequency of computer use	1 (every day) to 4 (almost never); reverse order
	Frequency of simple Internet use	1 (never) to 5 (every day)	Use of email	Yes/No
	Frequency of text-processing program use, e.g. Word	1 (never) to 5 (every day)	Search info on the Internet	Yes/No
	Frequency of real-time discussions through ICT devices	1 (never) to 5 (every day)	Data entry	Yes/No
	Frequency of reading letters, emails, memos	1 (never) to 5 (every day)	Word processing	Yes/No
	Frequency of writing letters, emails, memos	1 (never) to 5 (every day)	Use of spreadsheets	Yes/No
	Level of computer use required for the job	1 (normal) to 3 (complex)	Use of databases	Yes/No
			Use of software packs, design of websites, or programming	Yes/No
			Use of macros and complex equations	Yes/No
			Use of accounting or financial software	Yes/No
			Use of presentation or graphics software	Yes/No
			Use of website designing programs	Yes/No
			Use of CAD software	Yes/No
			Use of of statistical or other type of analysis	Yes/No
			Use of software programming	Yes/No
			Use of computer network management	Yes/No
Managerial and communication	Frequency of negotiating with people inside or outside the firm or organization	1 (never) to 5 (every day)	Contacting people other than co-workers (e.g., customers, clients, students, members of the public)	Yes/No
	Frequency of planning activities of others	1 (never) to 5 (every day)	Meet or interact for at least 10-15 minutes at a time with a customer, client, student or the public	1 (few times) to 10 (most of the time)
	Frequency of instructing and teaching people	1 (never) to 5 (every day)	Make formal presentations to clients or colleagues to provide information or persuade them of your point of view	Yes/No
	Frequency of advising people	1 (never) to 5 (every day)	Direct and check the work of other workers (supervise)	Yes/No
	Frequency of persuading or influencing others	1 (never) to 5 (every day)		

Table A1 cont.

Skill measure	PIAAC		STEP	
	Questions used	Metric	Questions used	Metric
Readiness to learn and creative problem-solving	I like to get to the bottom of difficult things	1 (not at all) to 5 (to a very high extent)	Engage in tasks that involve 30 or more minutes of thinking	1 (never) to 5 (every day)
	If I don't understand something, I look for additional information to make it clearer	1 (not at all) to 5 (to a very high extent)	Learning new things	1 (every day) to 5 (rarely or never); reverse order
	When I come across something new, I try to relate to what I already know	1 (not at all) to 5 (to a very high extent)	Come up with ideas other people haven't thought of before	1 (almost always) to 4 (almost never); reverse order
	When I hear or read about new ideas, I try to relate them to real life situations to which they might apply	1 (not at all) to 5 (to a very high extent)	Finish whatever you begin	1 (almost always) to 4 (almost never); reverse order
	I like learning new things	1 (not at all) to 5 (to a very high extent)	Think carefully before you make an important decision	1 (almost always) to 4 (almost never); reverse order
	I like to figure out how different ideas fit together	1 (not at all) to 5 (to a very high extent)	Work very hard, such as continuing to work when others stop to take a break	1 (almost always) to 4 (almost never); reverse order
			Be very interested in learning new things	1 (almost always) to 4 (almost never); reverse order
			Ask for help when don't understand something	1 (almost always) to 4 (almost never); reverse order
Self-organization	Extent of own planning of the task sequences	1 (not at all) to 5 (to a very high extent)	Freedom to decide how to do your work in your own way, rather than following a fixed procedure or a supervisor's instructions	1 (no freedom) to 10 (complete freedom)
	Extent of own planning of style of work	1 (not at all) to 5 (to a very high extent)		
	Extent of own planning of speed of work	1 (not at all) to 5 (to a very high extent)		
	Extent of own planning of working hours	1 (not at all) to 5 (to a very high extent)		
Marketing and accounting	Frequency of reading financial invoices, bills, etc.	1 (never) to 5 (every day)	Read bills or financial statements	Yes/No
	Frequency of calculating prices, costs, or budgets	1 (never) to 5 (every day)	Calculate prices or costs	Yes/No
	Frequency of using a calculator	1 (never) to 5 (every day)		
	Frequency of selling a product or a service	1 (never) to 5 (every day)		
STEM quantitative skills	Frequency of preparing charts and tables	1 (never) to 5 (every day)	Measure sizes, weights, distances	Yes/No
	Frequency of use of simple algebra and formulas	1 (never) to 5 (every day)	Use or calculate fractions or decimals	Yes/No
	Frequency of use of complex algebra and statistics	1 (never) to 5 (every day)	Perform any other multiplication or division	Yes/No
			Advanced math	Yes/No

Source: Own elaboration based on PIAAC and STEP surveys.
Notes: *Reverse order* means we reversed the order of the categories such that a higher value mean higher frequency of the task.

Table A2. Average Number of Operation Robots Over 2011-2014

	Latin America	USA	Western Europe
Agriculture, forestry and fishing	2.6	54.0	30.9
Mining and quarrying	1.9	11.0	8.1
Manufacturing	1,457	146,608	22,023
Electricity, gas, water supply	0.3	7.8	12.7
Construction	1.5	105.3	60.9
Education and Research development	5.4	328.3	212.5
All other non-manufacturing branches	3.5	189.3	26.4

Source: Own elaboration based on International Federation of Robotics.
Note: For Latin America and Western Europe, the table shows the cross-country average from 2011 to 2014.

APPENDIX B: Complete Estimation Results

Table B1. Returns to Skills

	Dependent variable: Log of hourly wages (in USD at PPP of 2005)											
	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
Age	-0.00736	0.0284	0.00126	0.0393	-0.00166	0.0346	0.000304	0.0413	0.0044	0.0417	-0.00123	0.0362
	[0.0105]	[0.00799]***	[0.0107]	[0.00812]***	[0.0106]	[0.00798]***	[0.0107]	[0.00810]***	[0.0108]	[0.00809]***	[0.0107]	[0.00799]***
Age sq	0.00015	-0.000265	3.69E-05	-0.00039	7.30E-05	-0.000344	3.62E-05	-0.000423	-7.98E-06	-0.000425	7.14E-05	-0.000355
	[0.000137]	0.000101]**	[0.000141]	0.000103]**	[0.000138]	0.000101]**	[0.000140]	0.000103]**	[0.000141]	0.000103]**	[0.000141]	0.000101]**
=1 if high-educated	0.293	0.254	0.398	0.349	0.322	0.291	0.405	0.357	0.424	0.361	0.377	0.308
	[0.0435]***	[0.0348]***	[0.0415]***	[0.0340]***	[0.0432]***	[0.0341]***	[0.0407]***	[0.0336]***	[0.0413]***	[0.0340]***	[0.0426]***	[0.0339]***
ICT skills	0.168	0.174										
	[0.0197]***	[0.0156]***										
Readiness to learn			0.066	0.0725								
			[0.0189]***	[0.0146]***								
Management and communication					0.142	0.141						
					[0.0190]***	[0.0150]***						
Self-organization							0.0941	0.0798				
							[0.0175]***	[0.0153]***				
Marketing and accounting									-0.000929	0.0549		
									[0.0184]	[0.0155]***		
STEM-quantitative											0.0852	0.152
											[0.0199]***	[0.0153]***
Constant	0.536	0.0145	0.298	-0.243	0.407	-0.11	0.364	-0.119	0.23	-0.283	0.369	-0.164
	[0.191]***	[0.152]	[0.194]	[0.153]	[0.192]**	[0.152]	[0.197]*	[0.151]	[0.193]	[0.154]*	[0.193]*	[0.152]
Observations	1,434	1,808	1,434	1,808	1,434	1,808	1,427	1,798	1,434	1,808	1,434	1,808
R-squared	0.335	0.353	0.303	0.318	0.325	0.341	0.309	0.316	0.297	0.314	0.306	0.349
Countries FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration based on PIAAC and STEP surveys.

Notes: Ordinary least squares regressions. Robust standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

PPP: Purchasing power parity.

Table B2. Returns to Skills in Sectors with Varying Digital Intensity

	Dependent variable: Log of hourly wages (in USD at PPP of 2005)											
	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
Age	-0.00755	0.0276	0.00156	0.0394	-0.0014	0.0343	0.000172	0.0415	0.00419	0.0418	-0.00114	0.0362
	[0.0105]	[0.00801]***	[0.0107]	[0.00812]***	[0.0106]	[0.00798]***	[0.0107]	[0.00810]***	[0.0108]	[0.00810]***	[0.0107]	[0.00799]***
Age sq	0.000152	-0.000255	3.42E-05	-0.00039	6.96E-05	-0.00034	4.01E-05	-0.000426	-3.16E-06	-0.000425	7.10E-05	-0.000355
	[0.000138]	[0.000101]**	[0.000141]	[0.000103]**	[0.000139]	[0.000101]**	[0.000141]	[0.000103]**	[0.000141]	[0.000103]**	[0.000141]	[0.000101]***
=1 if high-educated	0.293	0.263	0.397	0.35	0.321	0.299	0.396	0.357	0.421	0.363	0.376	0.305
	[0.0436]***	[0.0352]***	[0.0417]***	[0.0344]***	[0.0433]***	[0.0342]***	[0.0412]***	[0.0342]***	[0.0413]***	[0.0344]***	[0.0427]***	[0.0344]***
=1 if digital intensive sector	-0.0123	-0.0436	0.0224	-0.000451	0.00673	-0.0363	0.0204	0.0036	0.0236	-0.0032	0.0204	0.0108
	[0.0356]	[0.0309]	[0.0357]	[0.0315]	[0.0353]	[0.0314]	[0.0357]	[0.0314]	[0.0371]	[0.0319]	[0.0362]	[0.0308]
ICT skills	0.173	0.161										
	[0.0301]***	[0.0219]***										
ICT skills	-0.00758	0.0341										
=1 if digital-intensive sector	[0.0381]	[0.0302]										
Readiness to learn			0.0579	0.0686								
			[0.0250]**	[0.0198]***								
Readiness to learn *			0.0153	0.00803								
=1 if digital-intensive sector			[0.0362]	[0.0284]								
Management and communication					0.153	0.139						
					[0.0257]***	[0.0213]***						
Management and communication *					-0.0218	0.0105						
=1 if digital-intensive sector					[0.0356]	[0.0300]						
Self-organization							0.13	0.0604				
							[0.0246]***	[0.0218]***				
Self-organization							-0.0689	0.0389				
=1 if digital-intensive sector							[0.0352]*	[0.0305]				
Marketing and accounting									-0.0474	0.0409		
									[0.0275]*	[0.0230]*		
Marketing and accounting									0.0794	0.0276		
=1 if digital-intensive sector									[0.0370]**	[0.0311]		
STEM-quantitative											0.07	0.15
											[0.0317]**	[0.0227]***
STEM-quantitative											0.0268	0.00342
=1 if digital-intensive sector											[0.0392]	[0.0298]
Constant	0.546	0.0447	0.282	-0.245	0.402	-0.0874	0.365	-0.121	0.212	-0.285	0.356	-0.169
	[0.193]***	[0.154]	[0.194]	[0.154]	[0.193]**	[0.153]	[0.199]*	[0.152]	[0.193]	[0.155]*	[0.194]*	[0.153]
Observations	1,434	1,808	1,434	1,808	1,434	1,808	1,427	1,798	1,434	1,808	1,434	1,808
R-squared	0.335	0.354	0.303	0.318	0.325	0.342	0.311	0.317	0.3	0.315	0.306	0.349
Countries FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration based on PIAAC and STEP surveys.
Notes: Ordinary least squares regressions. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1
PPP: Purchasing power parity.

Table B3. Returns to Skills: Heterogeneous Effects by Education

	Dependent variable: Log of hourly wages (in USD at PPP of 2005)											
	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
Age	-0.00781	0.0272	0.0014	0.0396	-0.00208	0.035	0.000113	0.0421	0.00436	0.0418	-0.00167	0.0361
	[0.0105]	[0.00797]***	[0.0107]	[0.00814]***	[0.0106]	[0.00794]***	[0.0107]	[0.00804]***	[0.0108]	[0.00805]***	[0.0107]	[0.00798]***
Age sq	0.000155	-0.00025	3.47E-05	-0.000395	7.81E-05	-0.00035	3.92E-05	-0.000434	-7.45E-06	-0.000427	7.67E-05	-0.000354
	[0.000137]	[0.000101]**	[0.000141]	[0.000104]**	[0.000138]	[0.000100]**	[0.000140]	[0.000102]**	[0.000142]	[0.000102]**	[0.000141]	[0.000101]**
=1 if high-educated	0.336	0.309	0.394	0.354	0.338	0.341	0.411	0.364	0.424	0.379	0.407	0.319
	[0.0533]***	[0.0374]***	[0.0435]***	[0.0345]***	[0.0491]***	[0.0347]***	[0.0420]***	[0.0337]***	[0.0415]***	[0.0340]***	[0.0492]***	[0.0339]***
ICT skills	0.104	0.0491										
	[0.0496]**	[0.0311]										
ICT skills	0.0737	0.159										
=1 if high-educated	[0.0543]	[0.0358]***										
Readiness to learn			0.0796	0.0498								
			[0.0330]**	[0.0222]**								
Readiness to learn *			-0.0178	0.035								
=1 if high-educated			[0.0397]	[0.0288]								
Management and communication					0.114	-0.00144						
					[0.0388]***	[0.0273]						
Management and communication *					0.035	0.19						
=1 if high-educated					[0.0442]	[0.0327]***						
Self-organization							0.0591	0.00947				
							[0.0349]*	[0.0243]				
Self-organization							0.0454	0.107				
=1 if high-educated							[0.0402]	[0.0310]***				
Marketing and accounting									-0.00326	-0.0149		
									[0.0317]	[0.0261]		
Marketing and accounting									0.00302	0.0964		
=1 if high-educated									[0.0380]	[0.0318]***		
STEM-quantitative											0.0377	0.0848
											[0.0490]	[0.0316]***
STEM-quantitative											0.0522	0.0813
=1 if high-educated											[0.0533]	[0.0359]**
Constant	0.504	-0.0242	0.301	-0.253	0.398	-0.18	0.361	-0.137	0.23	-0.303	0.347	-0.176
	[0.192]***	[0.152]	[0.194]	[0.154]	[0.193]**	[0.150]	[0.197]*	[0.151]	[0.194]	[0.152]**	[0.192]*	[0.152]
Observations	1,434	1,808	1,434	1,808	1,434	1,808	1,427	1,798	1,434	1,808	1,434	1,808
R-squared	0.336	0.359	0.303	0.319	0.325	0.352	0.31	0.321	0.297	0.317	0.306	0.35
Countries FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration based on PIAAC and STEP surveys.

Notes: Ordinary least squares regressions. Robust standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

PPP: Purchasing power parity.

Table B4. Returns to Skills: Correcting for Selection in the Labor Market

	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
Regression equation												
Dependent variable: Log of hourly wages (in USD at PPP of 2005)												
Age	0.00349	0.0284	0.00845	0.0393	0.00518	0.0346	0.00772	0.0413	0.0131	0.0417	0.00748	0.0362
	[0.0163]	[0.00799]***	[0.0148]	[0.00812]***	[0.0143]	[0.00798]***	[0.0139]	[0.00810]***	[0.0153]	[0.00809]***	[0.0151]	[0.00799]***
Age sq	9.47E-05	-0.000265	2.15E-05	-0.00039	6.28E-05	-0.000344	1.70E-05	-0.000423	-3.44E-05	-0.000425	4.02E-05	-0.000355
	[0.000208]	[0.000101]**	[0.000189]	[0.000103]**	[0.000182]	[0.000101]**	[0.000177]	[0.000103]**	[0.000195]	[0.000103]**	[0.000193]	[0.000101]**
=1 if high-educated	0.298	0.254	0.419	0.349	0.309	0.291	0.432	0.357	0.437	0.361	0.393	0.308
	[0.0708]***	[0.0348]***	[0.0616]***	[0.0340]***	[0.0619]***	[0.0341]***	[0.0574]***	[0.0336]***	[0.0637]***	[0.0340]***	[0.0641]***	[0.0339]***
ICT skills	0.188	0.174										
	[0.0289]***	[0.0156]***										
Readiness to learn			0.0697	0.0725								
			[0.0256]***	[0.0146]***								
Management and communication					0.176	0.141						
					[0.0250]***	[0.0150]***						
Self-organization							0.0754	0.0798				
							[0.0223]***	[0.0153]***				
Marketing and accounting									0.0271	0.0549		
									[0.0256]	[0.0155]***		
STEM-quantitative											0.0948	0.152
											[0.0276]***	[0.0153]***
Constant	0.261	0.0145	0.0835	-0.243	0.219	-0.11	0.117	-0.119	-0.0187	-0.283	0.113	-0.164
	[0.306]	[0.152]	[0.277]	[0.153]	[0.268]	[0.152]	[0.261]	[0.151]	[0.285]	[0.154]*	[0.283]	[0.152]
Observations	1,220	1,808	1,220	1,808	1,220	1,808	1,213	1,798	1,220	1,808	1,220	1,808
Selection equation												
Dependent variable: =1 if actively participating in labor market												
Age	0.188		0.188		0.188		0.188		0.188		0.188	
	[0.0522]***		[0.0522]***		[0.0522]***		[0.0522]***		[0.0522]***		[0.0522]***	
Age sq	-0.00185		-0.00185		-0.00185		-0.00185		-0.00185		-0.00185	
	[0.000645]***		[0.000645]***		[0.000645]***		[0.000645]***		[0.000645]***		[0.000645]***	
=1 if high-educated	-0.117		-0.117		-0.117		-0.117		-0.117		-0.117	
	[0.221]		[0.221]		[0.221]		[0.221]		[0.221]		[0.221]	
Number of children	-0.21		-0.21		-0.21		-0.21		-0.21		-0.21	
	[0.0903]**		[0.0903]**		[0.0903]**		[0.0903]**		[0.0903]**		[0.0903]**	
Lambda	0.95		0.86		0.84		0.81		0.90		0.88	
std. error.	0.40		0.36		0.35		0.34		0.37		0.37	
Countries FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration based on PIAAC and STEP surveys.

Notes: Heckman selection models. Robust standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

PPP: Purchasing power parity.

Table B5. Returns to Skills: Correcting for Selection in the Labor Market. Sectors with Varying Digital Intensity

	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
Regression equation												
Dependent variable: Log of hourly wages (in USD at PPP of 2005)												
Age	0.0033	0.0276	0.00861	0.0394	0.00543	0.0343	0.00737	0.0415	0.013	0.0418	0.00753	0.0362
	[0.0165]	[0.00801]***	[0.0146]	[0.00812]***	[0.0142]	[0.00798]***	[0.0132]	[0.00810]***	[0.0152]	[0.00810]***	[0.0150]	[0.00799]***
Age sq	9.66E-05	-0.000255	2.02E-05	-0.00039	5.97E-05	-0.00034	2.30E-05	-0.000426	-3.17E-05	-0.000425	4.04E-05	-0.000355
	[0.000210]	[0.000101]**	[0.000187]	[0.000103]**	[0.000182]	[0.000101]**	[0.000169]	[0.000103]**	[0.000194]	[0.000103]**	[0.000192]	[0.000101]**
=1 if high-educated	0.299	0.263	0.417	0.35	0.308	0.299	0.423	0.357	0.433	0.363	0.391	0.305
	[0.0716]***	[0.0352]***	[0.0611]***	[0.0344]***	[0.0617]***	[0.0342]***	[0.0549]***	[0.0342]***	[0.0635]***	[0.0344]***	[0.0636]***	[0.0344]***
=1 if digital-intensive sector	-0.024	-0.0436	0.0287	-0.000451	0.00665	-0.0363	0.0236	0.0036	0.0135	-0.0032	0.0227	0.0108
	[0.0550]	[0.0309]	[0.0483]	[0.0315]	[0.0471]	[0.0314]	[0.0437]	[0.0314]	[0.0519]	[0.0319]	[0.0503]	[0.0308]
ICT skills	0.182	0.161										
	[0.0426]***	[0.0219]***										
ICT skills	0.0145	0.0341										
=1 if digital-intensive sector	[0.0555]	[0.0302]										
Readiness to learn			0.0668	0.0686								
			[0.0358]*	[0.0198]***								
Readiness to learn *			0.00576	0.00803								
=1 if digital-intensive sector			[0.0495]	[0.0284]								
Management and communication					0.183	0.139						
					[0.0345]***	[0.0213]***						
Management and communication *					-0.014	0.0105						
=1 if digital-intensive sector					[0.0473]	[0.0300]						
Self-organization							0.11	0.0604				
							[0.0301]***	[0.0218]***				
Self-organization *							-0.0688	0.0389				
=1 if digital-intensive sector							[0.0423]	[0.0305]				
Marketing and accounting									-0.0302	0.0409		
									[0.0380]	[0.0230]*		
Marketing and accounting *									0.104	0.0276		
=1 if digital-intensive sector									[0.0515]**	[0.0311]		
STEM-quantitative											0.0758	0.15
											[0.0400]*	[0.0227]***
STEM-quantitative *											0.0335	0.00342
=1 if digital-intensive sector											[0.0526]	[0.0298]
Constant	0.274	0.0447	0.066	-0.245	0.213	-0.0874	0.121	-0.121	-0.0377	-0.285	0.0989	-0.169
	[0.312]	[0.154]	[0.275]	[0.154]	[0.268]	[0.153]	[0.250]	[0.152]	[0.285]	[0.155]*	[0.282]	[0.153]
Observations	1,220	1,808	1,220	1,808	1,220	1,808	1,213	1,798	1,220	1,808	1,220	1,808
Selection equation												
Dependent variable: =1 if actively participating in labor market												
Age	0.188		0.188		0.188		0.188		0.188		0.188	
	[0.0522]***		[0.0522]***		[0.0522]***		[0.0522]***		[0.0522]***		[0.0522]***	
Age sq	-0.00185		-0.00185		-0.00185		-0.00185		-0.00185		-0.00185	
	[0.000645]***		[0.000645]***		[0.000645]***		[0.000645]***		[0.000645]***		[0.000645]***	
=1 if high-educated	-0.117		-0.117		-0.117		-0.117		-0.117		-0.117	
	[0.221]		[0.221]		[0.221]		[0.221]		[0.221]		[0.221]	
Number of children	-0.21		-0.21		-0.21		-0.21		-0.21		-0.21	
	[0.0903]**		[0.0903]**		[0.0903]**		[0.0903]**		[0.0903]**		[0.0903]**	
Observations	1,220		1,220		1,220		1,220		1,220		1,220	
Lambda	0.96		0.86		0.83		0.77		0.89		0.88	
std. error.	0.40		0.36		0.35		0.32		0.37		0.36	
Countries FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration based on PIAAC and STEP surveys.

Notes: Heckman selection models. Robust standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

PPP: Purchasing power parity.

Table B6. Returns to Skills: Correcting for Selection in the Labor Market. Heterogeneous Effects by Education

	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
Regression equation												
Dependent variable: Log of hourly wages (in USD at PPP of 2005)												
Age	0.00332	0.0272	0.00839	0.0396	0.00435	0.035	0.00768	0.0421	0.0126	0.0418	0.00686	0.0361
	[0.0163]	[0.00797]***	[0.0148]	[0.00814]***	[0.0143]	[0.00794]***	[0.0140]	[0.00804]***	[0.0152]	[0.00805]***	[0.0152]	[0.00798]***
Age sq	9.63E-05	-0.00025	2.24E-05	-0.000395	7.30E-05	-0.00035	1.83E-05	-0.000434	-2.84E-05	-0.000427	4.75E-05	-0.000354
	[0.000209]	[0.000101]**	[0.000190]	[0.000104]**	[0.000182]	[0.000100]**	[0.000178]	[0.000102]**	[0.000194]	[0.000102]**	[0.000194]	[0.000101]**
=1 if high-educated	0.332	0.309	0.422	0.354	0.343	0.341	0.436	0.364	0.441	0.379	0.425	0.319
	[0.0847]***	[0.0374]***	[0.0632]***	[0.0345]***	[0.0671]***	[0.0347]***	[0.0582]***	[0.0337]***	[0.0638]***	[0.0340]***	[0.0818]***	[0.0339]***
ICT skills	0.136	0.0491										
	[0.0757]*	[0.0311]										
ICT skills	0.0609	0.159										
=1 if high-educated	[0.0818]	[0.0358]***										
Management and communication			0.063	0.0498								
			[0.0502]	[0.0222]**								
Management and Communication *			0.00896	0.035								
=1 if high-educated			[0.0584]	[0.0288]								
Self-organization					0.116	-0.00144						
					[0.0537]**	[0.0273]						
Self-Organization					0.0766	0.19						
=1 if high-educated					[0.0607]	[0.0327]***						
Marketing and accounting							0.0529	0.00947				
							[0.0451]	[0.0243]				
Self-Organization							0.03	0.107				
=1 if high-educated							[0.0519]	[0.0310]***				
Marketing and Accounting									0.00132	-0.0149		
									[0.0499]	[0.0261]		
Marketing and Accounting									0.0345	0.0964		
=1 if high-educated									[0.0577]	[0.0318]***		
STEM-quantitative											0.0426	0.0848
											[0.0873]	[0.0316]***
STEM-quantitative											0.0583	0.0813
=1 if high-educated											[0.0919]	[0.0359]**
Constant	0.226	-0.0242	0.0818	-0.253	0.195	-0.18	0.113	-0.137	-0.0175	-0.303	0.0944	-0.176
	[0.310]	[0.152]	[0.278]	[0.154]	[0.268]	[0.150]	[0.263]	[0.151]	[0.284]	[0.152]**	[0.285]	[0.152]
Observations	1,220	1,808	1,220	1,808	1,220	1,808	1,213	1,798	1,220	1,808	1,220	1,808
Selection equation												
Dependent variable: =1 if actively participating in labor market												
Age	0.188		0.188		0.188		0.188		0.188		0.188	
	[0.0522]***		[0.0522]***		[0.0522]***		[0.0522]***		[0.0522]***		[0.0522]***	
Age sq	-0.00185		-0.00185		-0.00185		-0.00185		-0.00185		-0.00185	
	[0.000645]***		[0.000645]***		[0.000645]***		[0.000645]***		[0.000645]***		[0.000645]***	
=1 if high-educated	-0.117		-0.117		-0.117		-0.117		-0.117		-0.117	
	[0.221]		[0.221]		[0.221]		[0.221]		[0.221]		[0.221]	
Number of children	-0.21		-0.21		-0.21		-0.21		-0.21		-0.21	
	[0.0903]**		[0.0903]**		[0.0903]**		[0.0903]**		[0.0903]**		[0.0903]**	
Lambda	0.96		0.87		0.83		0.82		0.89		0.88	
std. error.	0.40		0.36		0.35		0.34		0.37		0.37	
Countries FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration based on PIAAC and STEP surveys.
Notes: Heckman selection models. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1
PPP: Purchasing power parity.

Table B7. Returns to Skills: Robustness Analysis. Constraining All the Coefficients to Be the Same for Men and Women with the Exception of Their Returns to Skills

	Dependent variable: Log of hourly wages (in USD at PPP of 2005)					
=1 if female	-0.174	-0.194	-0.185	-0.191	-0.198	-0.159
	[0.0226]***	[0.0232]***	[0.0228]***	[0.0233]***	[0.0234]***	[0.0232]***
Age	0.013	0.0228	0.019	0.0237	0.0255	0.0201
	[0.00637]**	[0.00649]***	[0.00638]***	[0.00646]***	[0.00649]***	[0.00640]***
Age sq	-8.64E-05	-0.000205	-0.000165	-0.000226	-0.000243	-0.000171
	[8.17e-05]	[8.37e-05]**	[8.18e-05]**	[8.30e-05]***	[8.34e-05]***	[8.24e-05]**
=1 if high-educated	0.267	0.369	0.303	0.376	0.385	0.335
	[0.0270]***	[0.0262]***	[0.0266]***	[0.0259]***	[0.0262]***	[0.0264]***
ICT skills	0.176					
	[0.0154]***					
ICT skills * =1 if female	-0.00628					
	[0.0236]					
Readiness to learn		0.0704				
		[0.0144]***				
Readiness to learn * =1 if female		-0.00289				
		[0.0229]				
Management and communication			0.143			
			[0.0150]***			
Management and communication * =1 if female			0.000503			
			[0.0230]			
Self-organization				0.0784		
				[0.0153]***		
Self-organization * =1 if female				0.0133		
				[0.0233]		
Marketing and accounting					0.0517	
					[0.0154]***	
Marketing and accounting * =1 if female					-0.0433	
					[0.0235]*	
STEM-quantitative						0.149
						[0.0152]***
STEM-quantitative * =1 if female						-0.0593
						[0.0241]**
Constant	0.325	0.0861	0.201	0.16	0.0348	0.142
	[0.119]***	[0.120]	[0.119]*	[0.118]	[0.120]	[0.119]
Observations	3,242	3,242	3,242	3,225	3,242	3,242
R-squared	0.345	0.31	0.333	0.312	0.305	0.328

Source: Own elaboration based on PIAAC and STEP surveys.
Notes: Ordinary least squares regressions. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1
PPP: Purchasing power parity.

Table B8. Returns to Skills: Robustness Analysis. Conditioning on Sectors and Occupations

	Dependent variable: Log of hourly wages (in USD at PPP of 2005)											
	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women	Men
Age	-0.0228	0.0159	-0.0205	0.0186	-0.0219	0.0167	-0.0226	0.0188	-0.0198	0.0193	-0.0207	0.0187
	[0.0101]**	[0.00741]**	[0.0102]**	[0.00739]**	[0.0102]**	[0.00733]**	[0.0102]**	[0.00735]**	[0.0102]*	[0.00737]***	[0.0102]**	[0.00736]**
Age sq	0.000319	-0.000122	0.000287	-0.000154	0.000305	-0.000133	0.000307	-0.000159	0.000273	-0.000164	0.000289	-0.000156
	[0.000131]**	[9.32e-05]	[0.000133]**	[9.30e-05]*	[0.000132]**	[9.21e-05]	[0.000132]**	[9.22e-05]*	[0.000131]**	[9.25e-05]*	[0.000131]**	[9.26e-05]*
=1 if high-educated	0.181	0.176	0.199	0.195	0.186	0.183	0.192	0.191	0.204	0.199	0.197	0.185
	[0.0459]***	[0.0339]***	[0.0458]***	[0.0337]***	[0.0462]***	[0.0335]***	[0.0458]***	[0.0336]***	[0.0457]***	[0.0335]***	[0.0462]***	[0.0334]***
ICT skills	0.0697	0.0713										
	[0.0224]***	[0.0167]***										
Readiness to learn			0.0154	0.0235								
			[0.0179]	[0.0133]*								
Management and communication					0.0516	0.0644						
					[0.0198]***	[0.0150]***						
Self-organization							0.0609	0.0402				
							[0.0167]***	[0.0140]***				
Marketing and accounting									-0.0373	0.0226		
									[0.0188]**	[0.0147]		
STEM-quantitative											0.0143	0.0607
											[0.0185]	[0.0149]***
Constant	1.726	1.143	1.721	1.131	1.692	1.147	1.869	1.141	1.75	1.112	1.722	1.092
	[0.258]***	[0.191]***	[0.259]***	[0.190]***	[0.258]***	[0.190]***	[0.266]***	[0.187]***	[0.262]***	[0.192]***	[0.259]***	[0.190]***
Observations	1,434	1,808	1,434	1,808	1,434	1,808	1,427	1,798	1,434	1,808	1,434	1,808
R-squared	0.445	0.485	0.44	0.481	0.443	0.485	0.445	0.48	0.442	0.48	0.44	0.485
Countries FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Occupation and sector FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration based on PIAAC and STEP surveys.

Notes: Ordinary least squares regressions. Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

PPP: Purchasing power parity.

Table B9. Returns to Skills: Robustness Analysis. Correcting for Selection in the Labor Market Using Different Exclusion-Restrictions. STEP Countries Only

Estimation Method:	OLS	Heckman	Heckman	Heckman
Exclusion-restriction:		Number of Children	Grandparents Presence	Both
Regression equation				
Dependent variable: Log of hourly wages (in USD at PPP of 2005)				
Age	-0.00390	-0.0163	-0.0355	-0.0246
	[0.0130]	[0.0351]	[0.0390]	[0.0322]
Age sq	0.000200	0.000271	0.000517	0.000378
	[0.000178]	[0.000451]	[0.000500]	[0.000413]
=1 if high-educated	0.233	0.136	0.116	0.128
	[0.0566]***	[0.0562]**	[0.0589]**	[0.0538]**
=1 if informal workers	-0.243	-0.227	-0.226	-0.226
	[0.0509]***	[0.0408]***	[0.0408]***	[0.0408]***
Number of children				
Grandmother/grandfather present				
ICT skills	0.142	0.112	0.112	0.112
	[0.0263]***	[0.0202]***	[0.0202]***	[0.0202]***
Readiness to learn				
Management and communication				
Self-organization				
Marketing and accounting				
STEM-quantitative				
Constant	0.604	0.967	1.464	1.181
	[0.241]**	[0.901]	[0.998]	[0.819]
Observations	715	3,184	3,184	3,184
Selection equation				
Dependent variable: =1 if actively participating in labor market				
Age		0.229	0.218	0.234
		[0.0125]***	[0.0114]***	[0.0127]***
Age sq		-0.00292	-0.00277	-0.00297
		[0.000161]***	[0.000146]***	[0.000162]***
=1 if high-educated		0.200	0.222	0.195
		[0.0509]***	[0.0501]***	[0.0510]***
Number of children		-0.0797		-0.0677
		[0.0228]***		[0.0234]***
Grandmother/grandfather present			0.181	0.143
			[0.0594]***	[0.0609]**
Occupation and sector dummies in reg. equation	No	No	No	No

Estimation Method:	OLS	Heckman	Heckman	Heckman
Exclusion-restriction:		Number of Children	Grandparents Presence	Both
Regression equation				
Dependent variable: Log of hourly wages (in USD at PPP of 2005)				
Age	-9.68e-06	-0.0266	-0.0439	-0.0349
	[0.0131]	[0.0356]	[0.0395]	[0.0327]
Age sq	0.000140	0.000401	0.000623	0.000508
	[0.000180]	[0.000458]	[0.000506]	[0.000419]
=1 if high-educated	0.313	0.167	0.149	0.158
	[0.0535]***	[0.0570]***	[0.0597]**	[0.0546]***
=1 if informal workers	-0.295	-0.264	-0.263	-0.263
	[0.0503]***	[0.0406]***	[0.0405]***	[0.0406]***
Number of children				
Grandmother/grandfather present				
ICT skills				
Readiness to learn	0.0432	0.0282	0.0274	0.0278
	[0.0237]*	[0.0176]	[0.0175]	[0.0176]
Management and communication				
Self-organization				
Marketing and accounting				
STEM-quantitative				
Constant	0.509	1.217	1.664	1.431
	[0.243]**	[0.914]	[1.010]*	[0.831]*
Observations	715	3,184	3,184	3,184
Selection equation				
Dependent variable: =1 if actively participating in labor market				
Age		0.229	0.218	0.234
		[0.0125]***	[0.0114]***	[0.0127]***
Age sq		-0.00292	-0.00277	-0.00297
		[0.000161]***	[0.000146]***	[0.000162]***
=1 if high-educated		0.200	0.222	0.195
		[0.0509]***	[0.0501]***	[0.0510]***
Number of children		-0.0797		-0.0677
		[0.0228]***		[0.0234]***
Grandmother/grandfather present			0.181	0.143
			[0.0594]***	[0.0609]**
Occupation and sector dummies in reg. equation	No	No	No	No

Estimation Method:	OLS	Heckman	Heckman	Heckman
Exclusion-restriction:		Number of Children	Grandparents Presence	Both
Regression equation				
Dependent variable: Log of hourly wages (in USD at PPP of 2005)				
Age	-0.00174	-0.0226	-0.0361	-0.0278
	[0.0131]	[0.0349]	[0.0386]	[0.0319]
Age sq	0.000159	0.000345	0.000517	0.000412
	[0.000179]	[0.000448]	[0.000496]	[0.000410]
=1 if high-educated	0.223	0.0994	0.0857	0.0943
	[0.0568]***	[0.0562]*	[0.0587]	[0.0537]*
=1 if informal workers	-0.252	-0.189	-0.188	-0.188
	[0.0497]***	[0.0411]***	[0.0410]***	[0.0411]***
Number of children				
Grandmother/grandfather present				
ICT skills				
Readiness to learn				
Management and communication	0.147	0.159	0.158	0.158
	[0.0242]***	[0.0203]***	[0.0203]***	[0.0203]***
Self-organization				
Marketing and accounting				
STEM-quantitative				
Constant	0.574	1.137	1.483	1.269
	[0.242]**	[0.895]	[0.989]	[0.813]
Observations	715	3,184	3,184	3,184
Selection equation				
Dependent variable: =1 if actively participating in labor market				
Age		0.229	0.218	0.234
		[0.0125]***	[0.0114]***	[0.0127]***
Age sq		-0.00292	-0.00277	-0.00297
		[0.000161]***	[0.000146]***	[0.000162]***
=1 if high-educated		0.200	0.222	0.195
		[0.0509]***	[0.0501]***	[0.0510]***
Number of children		-0.0797		-0.0677
		[0.0228]***		[0.0234]***
Grandmother/grandfather present			0.181	0.143
			[0.0594]***	[0.0609]**
Occupation and sector dummies in reg. equation	No	No	No	No

Estimation Method:	OLS	Heckman	Heckman	Heckman
Exclusion-restriction:		Number of Children	Grandparents Presence	Both
Regression equation				
Dependent variable: Log of hourly wages (in USD at PPP of 2005)				
Age	-0.00159	-0.0242	-0.0409	-0.0337
	[0.0131]	[0.0358]	[0.0388]	[0.0325]
Age sq	0.000148	0.000350	0.000565	0.000472
	[0.000179]	[0.000460]	[0.000498]	[0.000418]
=1 if high-educated	0.316	0.171	0.153	0.161
	[0.0531]***	[0.0568]***	[0.0590]***	[0.0542]***
=1 if informal workers	-0.317	-0.309	-0.308	-0.307
	[0.0503]***	[0.0411]***	[0.0411]***	[0.0411]***
Number of children				
Grandmother/grandfather present				
ICT skills				
Readiness to learn				
Management and communication				
Self-organization	0.0551	0.0827	0.0827	0.0827
	[0.0216]**	[0.0178]***	[0.0177]***	[0.0177]***
Marketing and accounting				
STEM-quantitative				
Constant	0.566	1.199	1.631	1.445
	[0.246]**	[0.922]	[0.997]	[0.831]*
Observations	708	3,173	3,173	3,173
Selection equation				
Dependent variable: =1 if actively participating in labor market				
Age		0.229	0.218	0.234
		[0.0125]***	[0.0114]***	[0.0127]***
Age sq		-0.00292	-0.00277	-0.00297
		[0.000161]***	[0.000146]***	[0.000162]***
=1 if high-educated		0.200	0.222	0.195
		[0.0509]***	[0.0501]***	[0.0510]***
Number of children		-0.0797		-0.0677
		[0.0228]***		[0.0234]***
Grandmother/grandfather present			0.181	0.143
			[0.0594]***	[0.0609]**
Occupation and sector dummies in reg. equation	No	No	No	No

Estimation Method:	OLS	Heckman	Heckman	Heckman
Exclusion-restriction:		Number of Children	Grandparents Presence	Both
Regression equation				
Dependent variable: Log of hourly wages (in USD at PPP of 2005)				
Age	0.000804	-0.0236	-0.0426	-0.0334
	[0.0131]	[0.0355]	[0.0395]	[0.0326]
Age sq	0.000127	0.000363	0.000605	0.000488
	[0.000180]	[0.000456]	[0.000506]	[0.000419]
=1 if high-educated	0.335	0.169	0.150	0.159
	[0.0526]***	[0.0566]***	[0.0596]**	[0.0544]***
=1 if informal workers	-0.307	-0.280	-0.279	-0.278
	[0.0500]***	[0.0406]***	[0.0406]***	[0.0406]***
Number of children				
Grandmother/grandfather present				
ICT skills				
Readiness to learn				
Management and communication				
Self-organization				
Marketing and accounting	-0.0205	0.0332	0.0329	0.0333
	[0.0230]	[0.0182]*	[0.0182]*	[0.0182]*
STEM-quantitative				
Constant	0.489	1.163	1.652	1.414
	[0.244]**	[0.912]	[1.010]	[0.831]*
Observations	715	3,184	3,184	3,184
Selection equation				
Dependent variable: =1 if actively participating in labor market				
Age		0.229	0.218	0.234
		[0.0125]***	[0.0114]***	[0.0127]***
Age sq		-0.00292	-0.00277	-0.00297
		[0.000161]***	[0.000146]***	[0.000162]***
=1 if high-educated		0.200	0.222	0.195
		[0.0509]***	[0.0501]***	[0.0510]***
Number of children		-0.0797		-0.0677
		[0.0228]***		[0.0234]***
Grandmother/grandfather present			0.181	0.143
			[0.0594]***	[0.0609]**
Occupation and sector dummies in reg. equation	No	No	No	No

Estimation Method:	OLS	Heckman	Heckman	Heckman
Exclusion-restriction:		Number of Children	Grandparents Presence	Both
Regression equation				
Dependent variable: Log of hourly wages (in USD at PPP of 2005)				
Age	-0.00202	-0.0251	-0.0467	-0.0359
	[0.0131]	[0.0355]	[0.0395]	[0.0326]
Age sq	0.000174	0.000381	0.000659	0.000520
	[0.000181]	[0.000456]	[0.000507]	[0.000419]
=1 if high-educated	0.302	0.160	0.137	0.148
	[0.0539]***	[0.0568]***	[0.0600]**	[0.0547]***
=1 if informal workers	-0.292	-0.262	-0.260	-0.260
	[0.0504]***	[0.0404]***	[0.0404]***	[0.0405]***
Number of children				
Grandmother/grandfather present				
ICT skills				
Readiness to learn				
Management and communication				
Self-organization				
Marketing and accounting				
STEM-quantitative	0.0570	0.0513	0.0517	0.0516
	[0.0248]**	[0.0195]***	[0.0195]***	[0.0195]***
Constant	0.547	1.189	1.748	1.468
	[0.244]**	[0.911]	[1.011]*	[0.831]*
Observations	715	3,184	3,184	3,184
Selection equation				
Dependent variable: =1 if actively participating in labor market				
Age		0.229	0.218	0.234
		[0.0125]***	[0.0114]***	[0.0127]***
Age sq		-0.00292	-0.00277	-0.00297
		[0.000161]***	[0.000146]***	[0.000162]***
=1 if high-educated		0.200	0.222	0.195
		[0.0509]***	[0.0501]***	[0.0510]***
Number of children		-0.0797		-0.0677
		[0.0228]***		[0.0234]***
Grandmother/grandfather present			0.181	0.143
			[0.0594]***	[0.0609]**
Occupation and sector dummies in reg. equation	No	No	No	No

Source: Own elaboration based on PIAAC and STEP surveys.

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.

PPP: Purchasing power parity.

Table B10. Oaxaca-Blinder Decomposition of the Gender Wage Gap

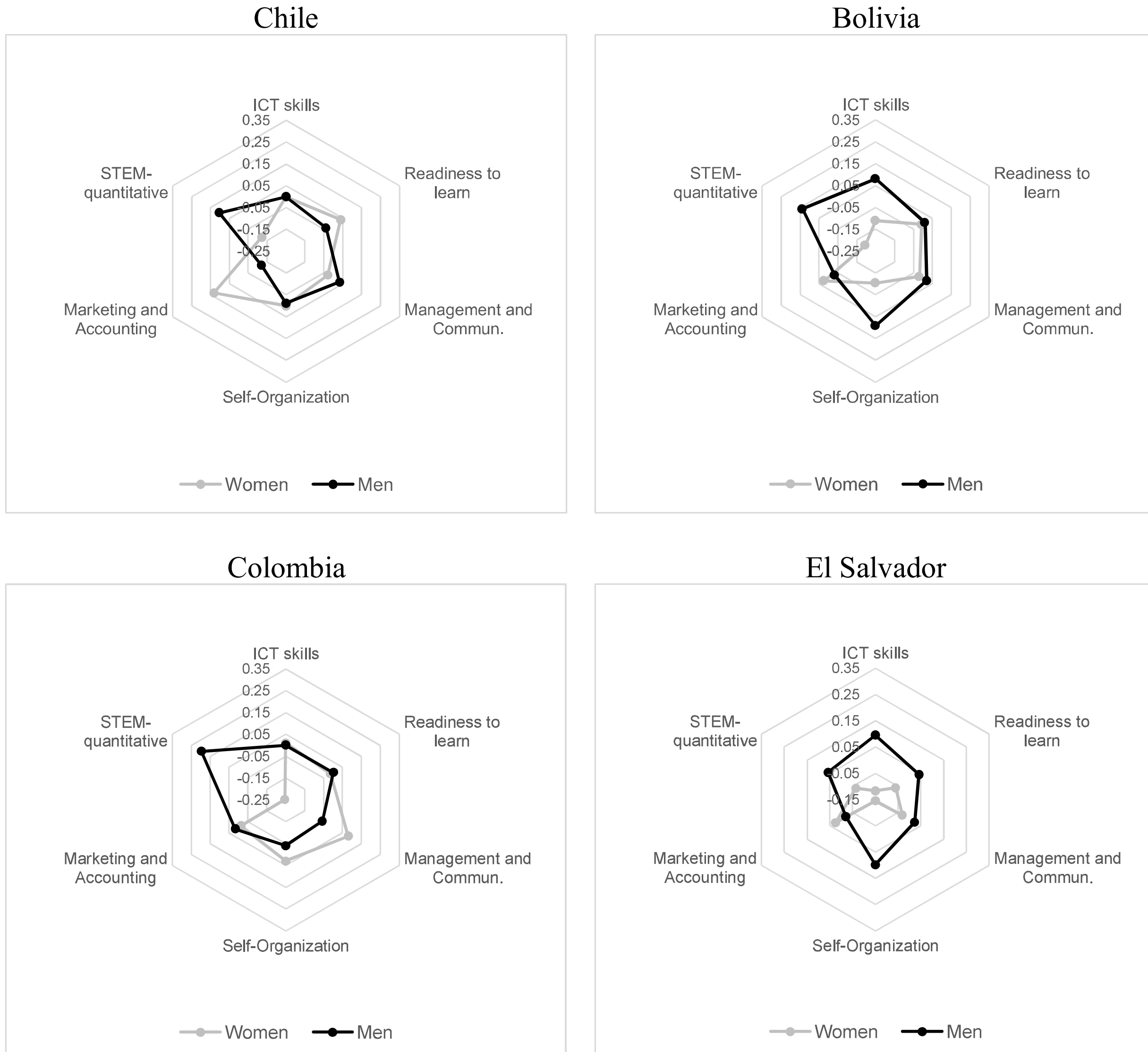
	Endowments	Coefficients	Endowments	Coefficients	Endowments	Coefficients	Endowments	Coefficients	Endowments	Coefficients	Endowments	Coefficients
Totals	**0.044**	**-0.174**	**0.0628**	**-0.193**	**0.054**	**-0.184**	**0.0589**	**-0.19**	**0.0703**	**-0.2**	**0.0176**	**-0.148**
	[0.0166]* **	**[0.0230]*** **	**[0.0156]*** **	**[0.0237]*** **	**[0.0160]*** **	**[0.0232]*** **	**[0.0156]*** **	**[0.0237]*** **	**[0.0156]*** **	**[0.0239]*** **	**[0.0169]**	**[0.0239]*** **
Other factors	0.0548	-0.696	0.0615	-0.734	0.0569	-0.701	0.0629	-0.673	0.063	-0.709	0.0586	-0.69
	[0.0147]***	[0.241]***	[0.0152]***	[0.245]***	[0.0147]***	[0.242]***	[0.0152]***	[0.246]***	[0.0153]***	[0.245]***	[0.0150]***	[0.242]***
ICT skills	-0.0108	-0.0118										
	[0.00621]*	[0.0501]										
Readiness to learn			0.00129	-0.0345								
			[0.00256]	[0.127]								
Management and communication					-0.00292	0.00127						
					[0.00500]	[0.0437]						
Self-organization							-0.00394	0.0337				
							[0.00293]	[0.0545]				
Marketing and accounting									0.00731	-0.0841		
									[0.00284]***	[0.0363]**		
STEM-quantitative											-0.041	-0.104
											[0.00667]***	[0.0394]***
Constant		0.534		0.576		0.516		0.449		0.593		0.647
		[0.243]**		[0.265]**		[0.244]**		[0.252]*		[0.252]**		[0.246]***
Observations	3,242	3,242	3,242	3,242	3,242	3,242	3,225	3,225	3,242	3,242	3,242	3,242
Countries FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Source: Own elaboration based on PIAAC and STEP surveys.

Notes: Robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1

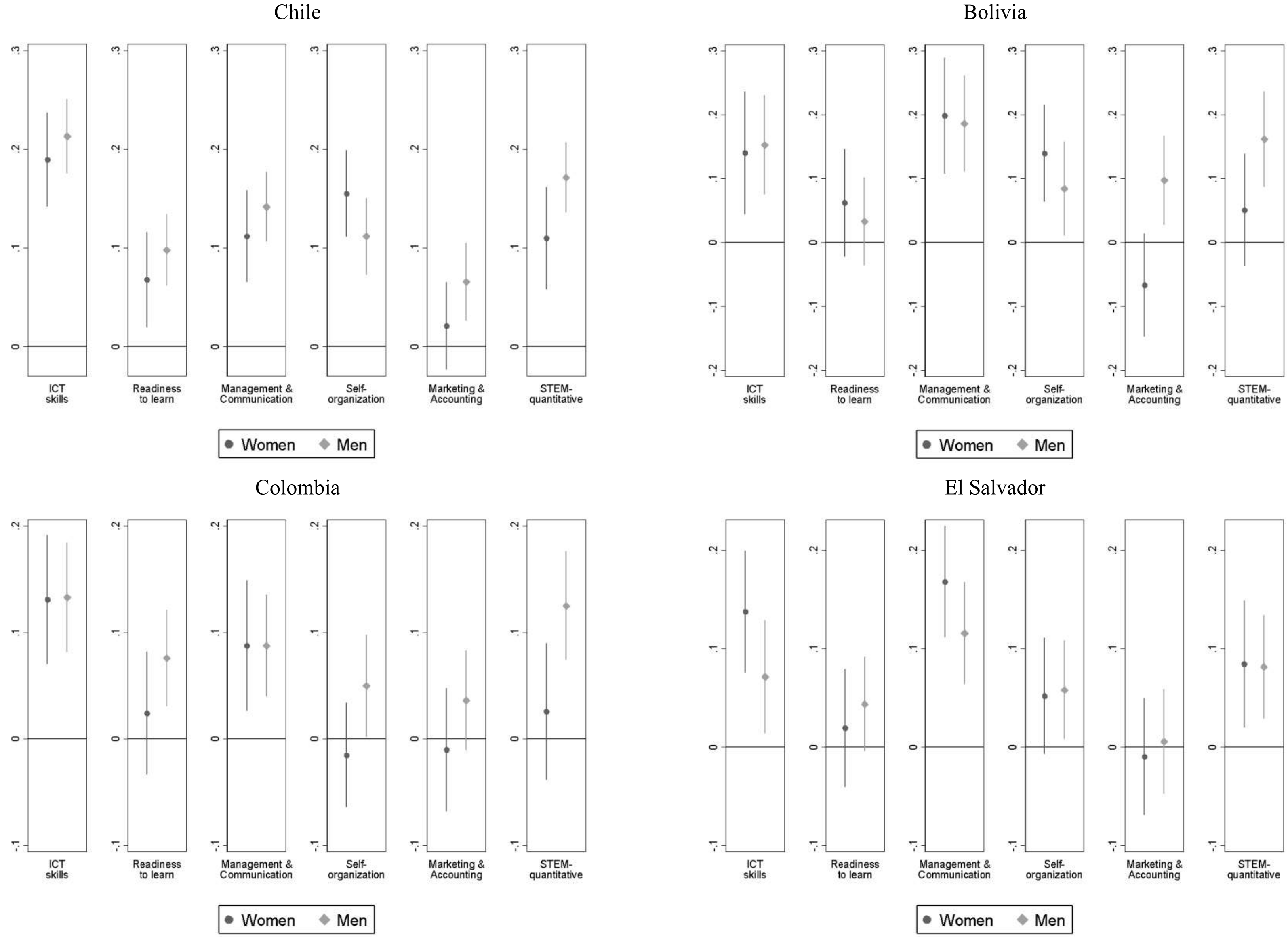
Appendix C

Figure C1. Skills in the Digital Economy



Source: Own elaboration based on PIAAC and STEP surveys.

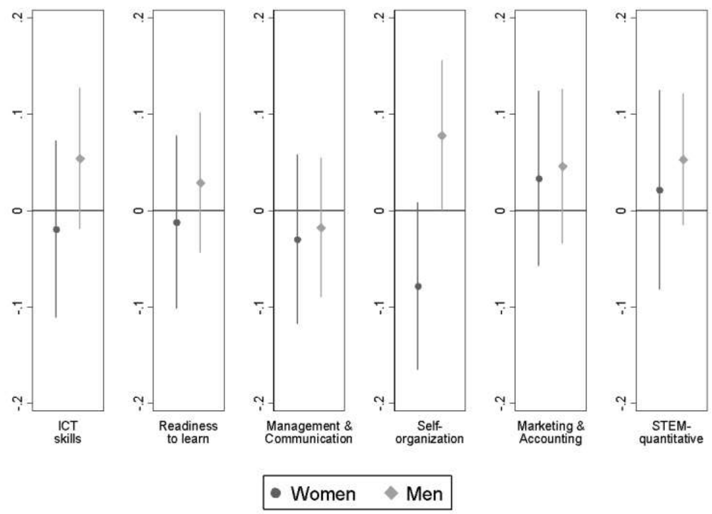
Figure C2: Returns to Skills



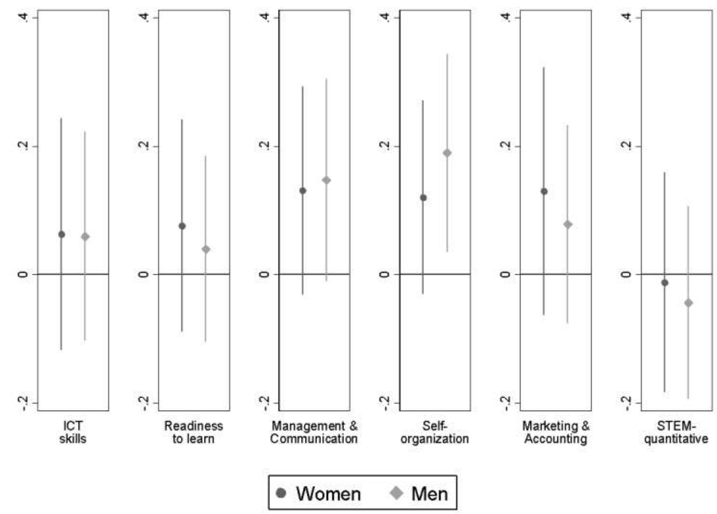
Source: Own elaboration based on PIAAC and STEP surveys.

Figure C3: Returns to Skills in Sectors with Varying Digital Intensity: Extra Returns for Working in Digital-Intensive Sectors

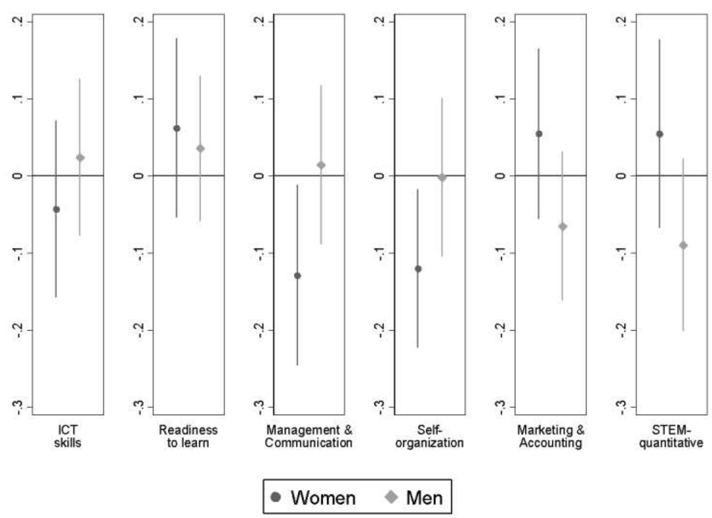
Chile



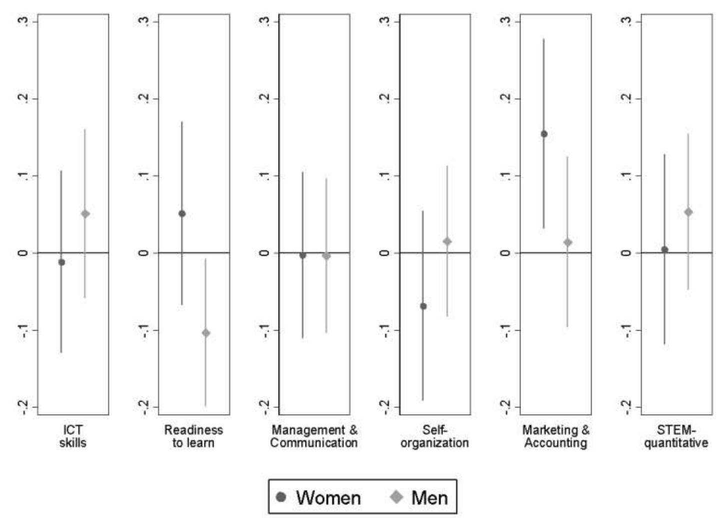
Bolivia



Colombia



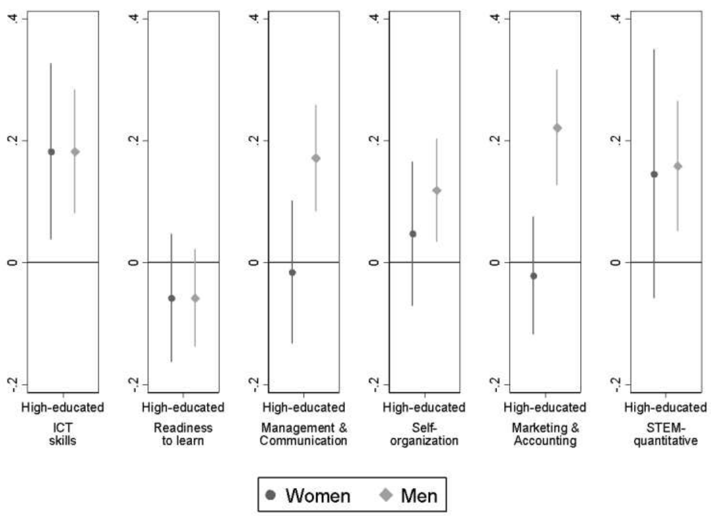
El Salvador



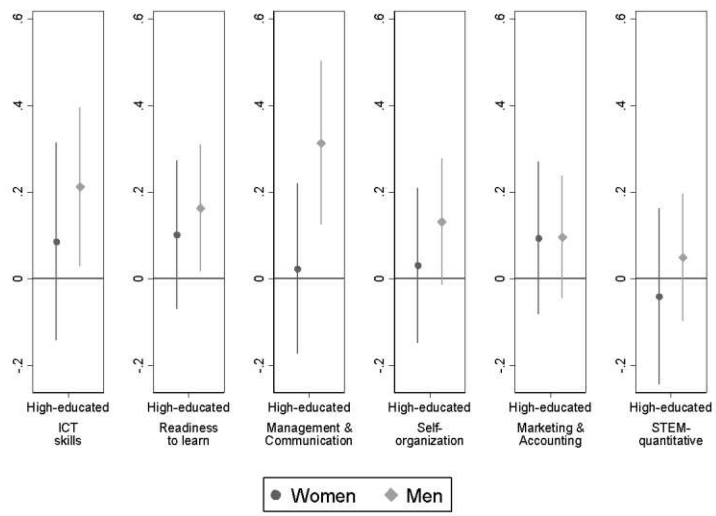
Source: Own elaboration based on PIAAC and STEP surveys.

Figure C4: Heterogeneous Effects by Education: Extra Returns for High-Educated Workers

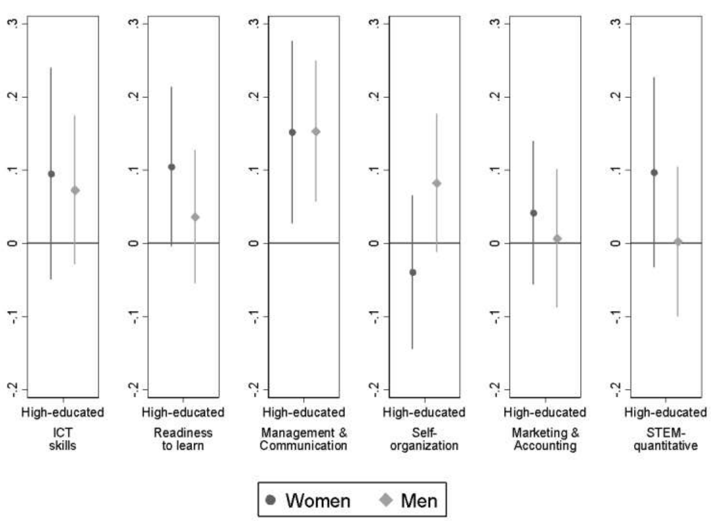
Chile



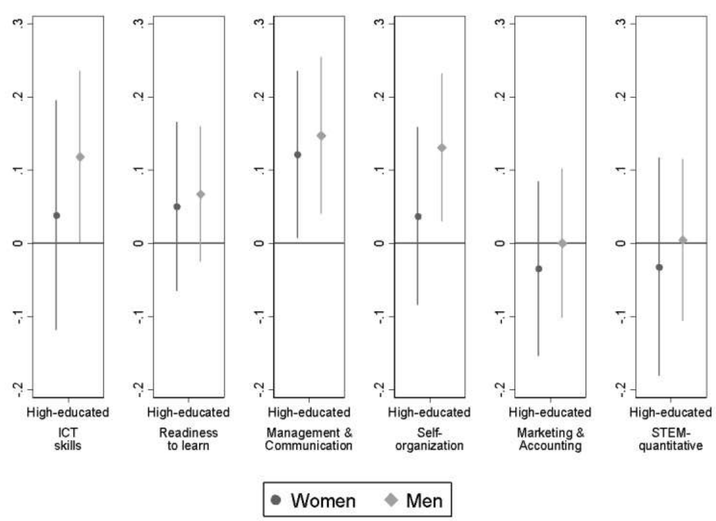
Bolivia



Colombia



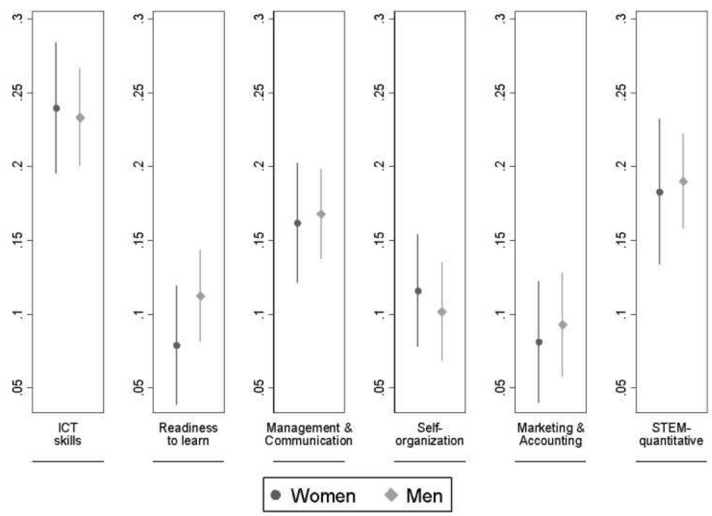
El Salvador



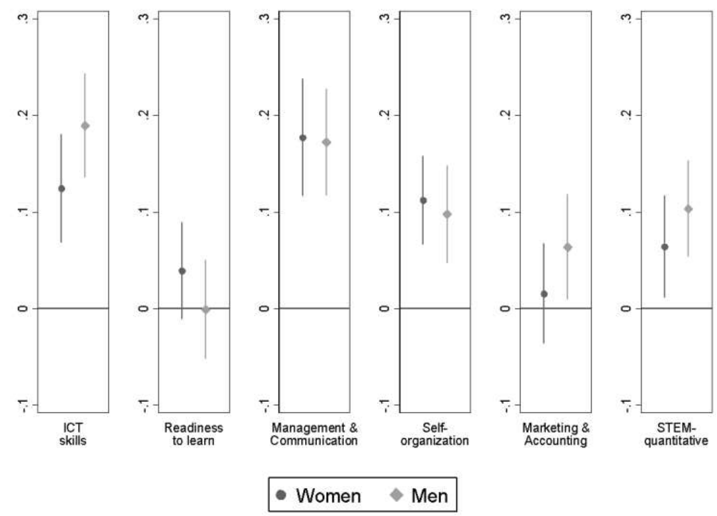
Source: Own elaboration based on PIAAC and STEP surveys.

Figure C5: Returns to Skills: Correcting for Selection in the Labor Market

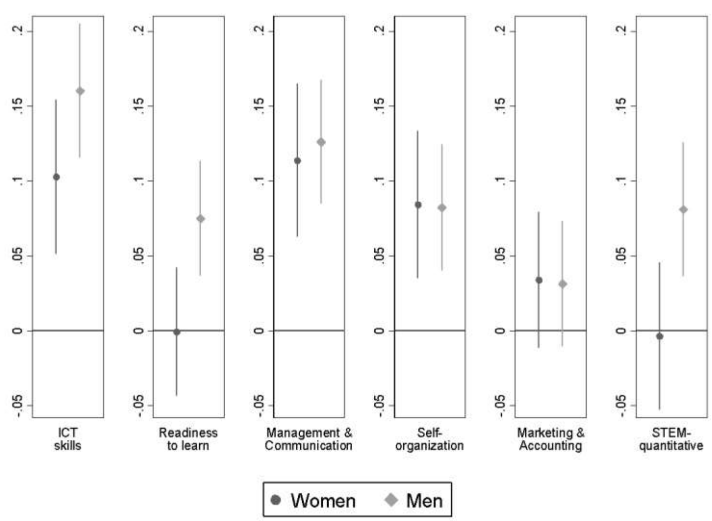
Chile



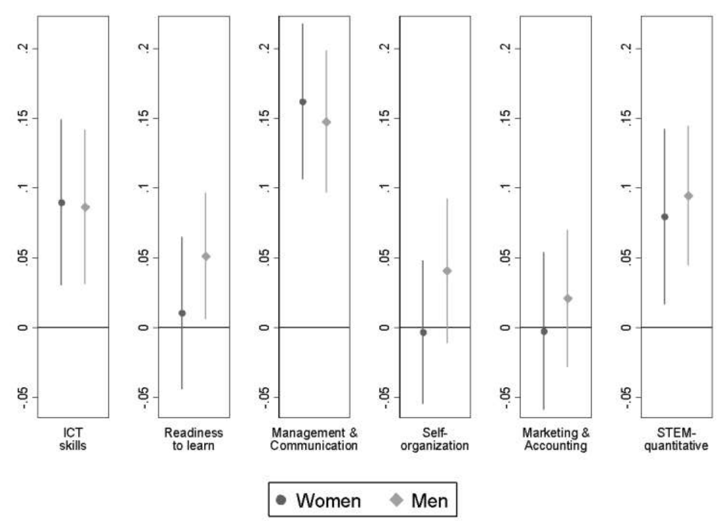
Bolivia



Colombia

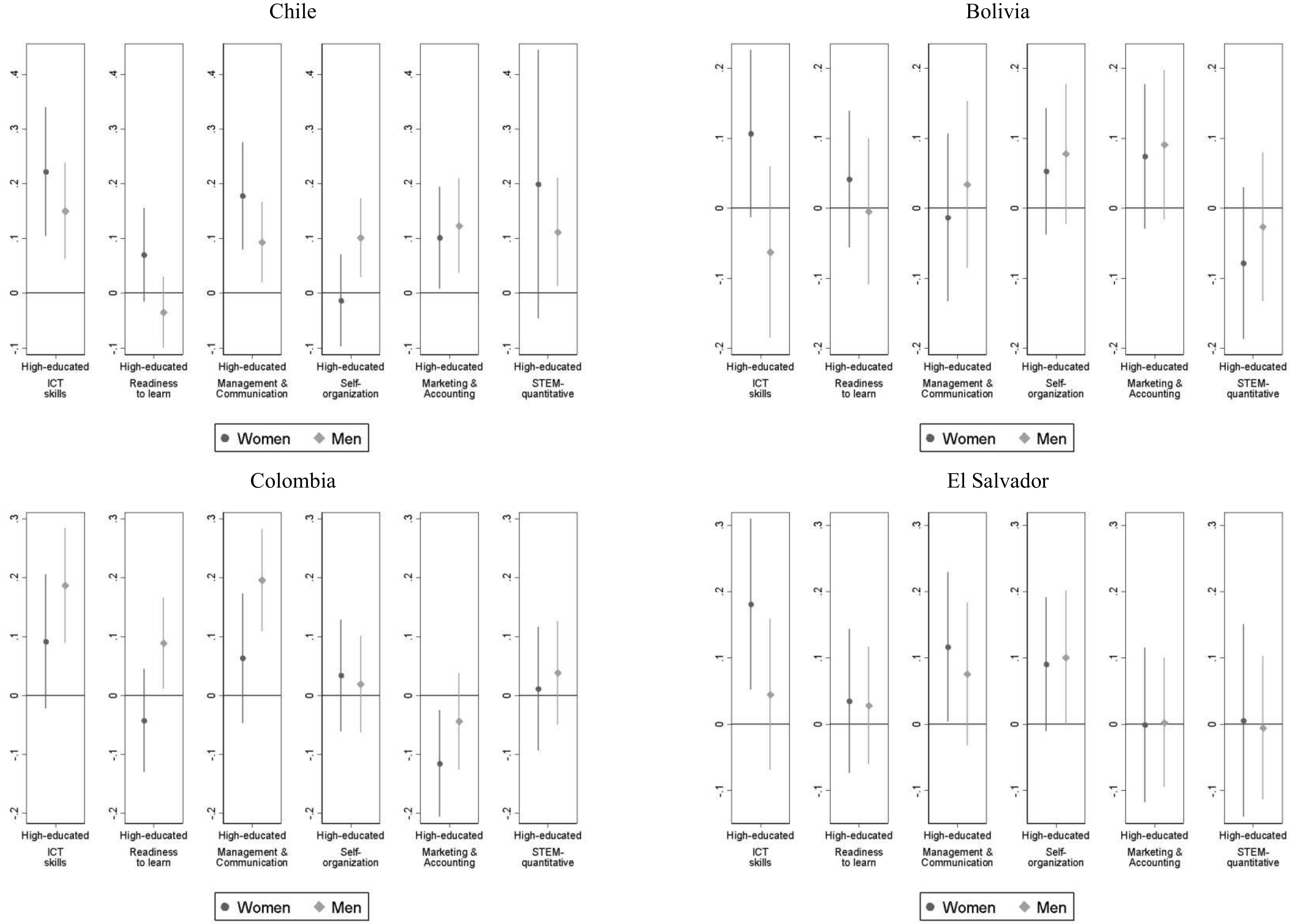


El Salvador



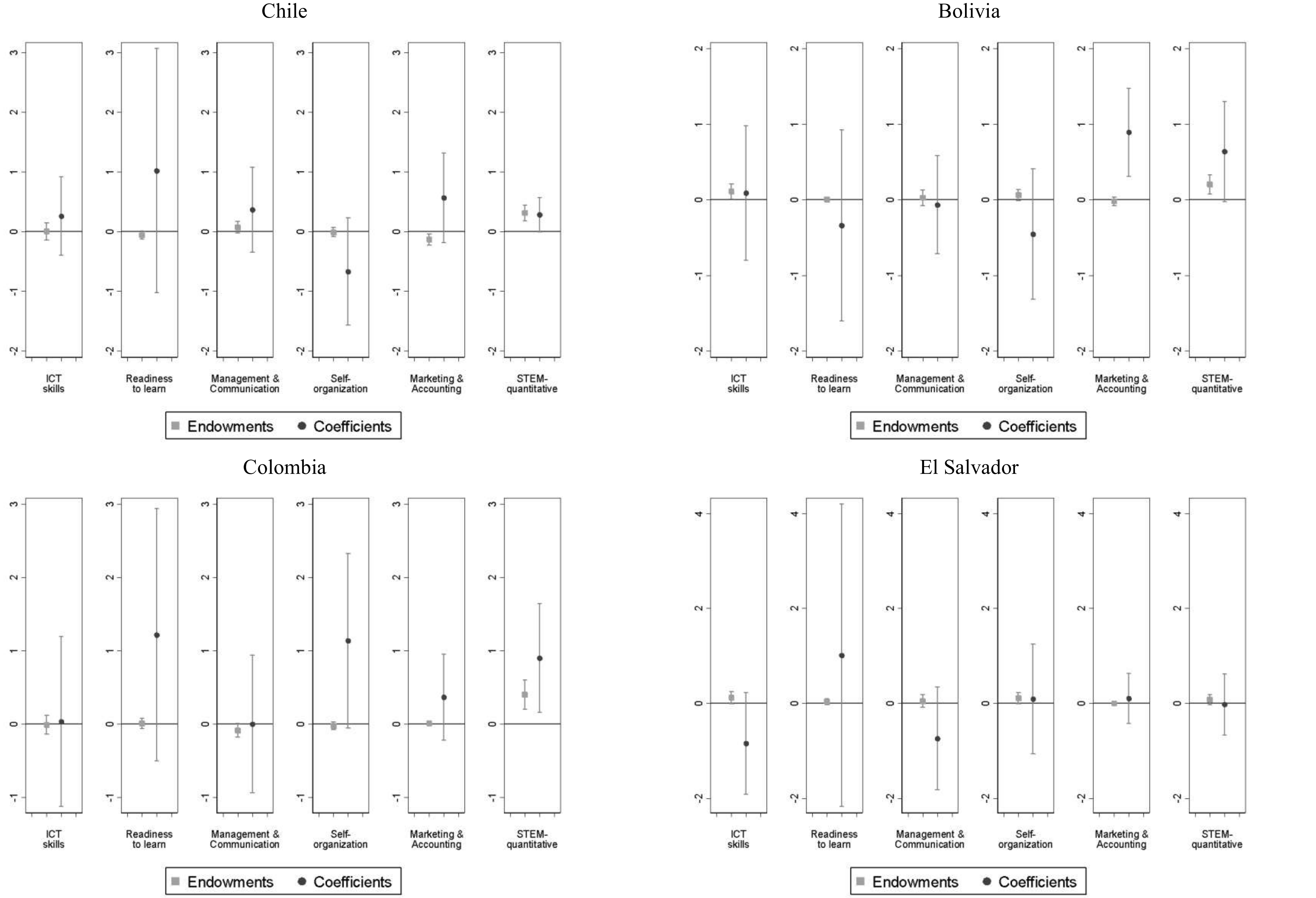
Source: Own elaboration based on PIAAC and STEP surveys.

Figure C6: Correcting for Selection in the Labor Market: Extra Returns for High-Educated Workers



Source: Own elaboration based on PIAAC and STEP surveys.

Figure C7: Oaxaca-Blinder Decomposition. Contribution of the Skills' Returns and Endowments to the Gender Wage Gap



Source: Own elaboration based on PIAAC and STEP surveys.