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Automation in Latin America: Are Women at Higher Risk of Losing Their Jobs?*

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Abstract

New technological trends, such as digitization, artificial intelligence and robotics, have the power to drastically increase economic output but may also displace workers. In this paper we assess the risk of automation for female and male workers in four Latin American countries – Bolivia, Chile, Colombia and El Salvador. Our study is the first to apply a task-based approach with a gender perspective in this region. Our main findings indicate that men are more likely than women to perform tasks linked to the 'skills of the future', such as STEM (science, technology, engineering and mathematics), information and communications technology, management and communication, and creative problem-solving tasks. Women thus have a higher average risk of automation, and 21% of women vs. 19% of men are at high risk (probability of automation greater than 70%). The differential impacts of the new technological trends for women and men must be assessed in order to guide the policy-making process to prepare workers for the future. Action should be taken to prevent digital transformation from worsening existing gender inequalities in the labor market.

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1. Introduction

Automation – i.e. artificial intelligence, digitalization, and robotization – is a type of labor market disruption that has the potential to create many opportunities to increase productivity, expand entrepreneurship, and drive inclusive economic growth. Prior research on the effects of automation on labor markets has predicted how many jobs will be created and destroyed (Winick, 2018), and its impacts on polarization (Autor, 2019). Yet enhancing economic growth and competitiveness requires not only technological advances, but also a labor force capable of handling the coming challenges of what has been referred to as the "Fourth Industrial Revolution" (4IR). Without a prepared workforce, automation will not advance development.

Will technology benefit or hurt traditionally disadvantaged groups? Identifying differences in the impacts on specific groups will inform the design of policies to improve the conditions of groups that are expected to be negatively impacted by technological changes.

In this study we focus on the gender consequences of automation in Latin American and the Caribbean (LAC). Similarly to other regions of the world, and despite important improvements in recent decades, labor markets in LAC are characterized by significant gender gaps. Women have lower participation rates, earn lower wages, work in different sectors and occupations, and hold fewer management positions than men (Scott et al., 2016; Marchionni et al., 2019a; Marchionni et al., 2019b). Moreover, even when they are employed in the same occupation, women and men perform different tasks, or the same tasks with different intensities, using a different set of skills. This is crucial to understanding the possible consequences of automation. Workers who perform tasks and use skills that are *complementary* to the technology can benefit from automation, while those who perform the activities and use the skills that are *substituted by* the technology are more likely to lose their jobs due to automation.

Given these gender-based inequalities in the labor market, it is relevant to explore the general effects of automation as well as the gender-disaggregated impacts. Are women more vulnerable than men to being displaced by technology in LAC countries? Will the adoption of new technologies erode the labor market gains obtained by women in recent decades? What policies can help close the gender gap when advanced technologies are adopted? We will address these questions and provide valuable evidence on the differential impacts of automation on women and men in the LAC region.

Since Frey and Osborne's (2013) seminal study in the United States, there has been a notable growth in the number of studies estimating the risk of automation or the percentage of workers at high risk of losing their jobs – i.e., a predicted probability of being displaced by automation over 70%. Past research, which has mainly focused on developed countries, reports that between 9 and 47% of workers face a high risk of losing their jobs to automation (Arntz et al., 2016; Zmanyica et al., 2017; Brown, et al., 2017; Nedelkoska and Quintini, 2018; Rabella, 2018; Servoz, 2019). There is limited evidence on the effects of automation on workers in developing economies, and whether automation will affect men and women differently. To our knowledge, our study is the first to analyze the gender dimension of automation in the LAC region. The evidence for other regions of the world is mixed and depends on the countries analyzed and the methodology applied. For Organisation for Economic Co-operation and Development (OECD) countries, the evidence generally shows that women face a greater risk of automation than men (Brussevich et al., 2018; PwC, 2018). However, some differences appear between OECD countries. For example, automation has been found to represent a greater threat for US men than women (Muro et al., 2019).

In order to understand how automation can affect labor markets in LAC, and how male and female workers can be impacted differently, we rely on available data for four countries of the region – Bolivia, Colombia, Chile and El Salvador – that have detailed information on tasks that workers perform in their jobs. We combine data from two surveys: (1) the Programme for the International Assessment of Adult Competencies (PIAAC) survey, available for Chile in 2014 and (2) the Skills Towards Employment and Productivity (STEP) survey, available for Colombia and Bolivia in 2012 and for El Salvador in 2013. We adapt Arntz et al.'s (2016) task-based approach to the LAC region and consider that automation can displace certain tasks within an occupation, rather than full occupations.

We use this approach to analyze two main outcomes. First, we calculate the average risk of automation and the share of workers at high risk of being displaced by technology for women and men, reporting the gender gap for the group of four countries and for each country separately. In a second step, we support our results by comparing the distribution of the risk of automation for women and men obtained using the task-based approach with those obtained using the occupation-based approach originally proposed by Frey and Osborne (2017), and by analyzing the marginal effect of task measures and other workers' observable characteristics on the risk of automation.

We contribute to the literature on the automation of jobs in three main ways. First, applying the task-based approach we predict the risk of automation at the worker level for a set of countries in the LAC region and we calculate the gender gap in the average risk of automation and in the percentage of workers at high risk of being displaced by technology. To our knowledge, no other study has applied the task-based approach to the LAC region with a gender perspective. Second, we construct a set of seven task measures, including tasks linked to the 'skills of the future' that are expected to *complement* the technology and those that are expected to be *substituted by* it. From a gender point of view, and as has been shown in Bustelo et al. (2019), this exercise identifies some tasks that are intensively performed by women and others that are carried out mainly by men. In a third contribution, we assess which factors contribute the most to the risk of automation, jointly analyzing the gender gaps on task measures and other workers' characteristics and the marginal effect of these variables on the risk of automation. Understanding the heterogeneous impacts of automation for women and men is relevant to developing policy to ameliorate the potential impacts of automation on future jobs.

Our findings indicate that overall, women are slightly more likely than men to have robotics or algorithms replace their work. Specifically, our estimations indicate that women have a slightly but statistically significant higher average risk of automation and that 21% of women and 19% of men are at high risk (defined as a probability of automation greater than 70%). This gender difference is mainly attributable to differences in tasks performed at work, which is consistent with the evidence found for OECD countries (Nedelkoska and Quintini, 2018). Men tend to be more involved in management and communication, information and communications technology (ICT), and science, technology, engineering and mathematics (STEM) quantitative tasks, while women tend to perform more routine activities such as tasks related to marketing and accounting. Behind the regional average we observe differences across countries, which largely reflect the different composition of tasks in occupations between them. We find that more women are at high risk of automation than men in Bolivia, Chile and Colombia, where the gender gaps oscillate between 3 percentage points in Chile to 19 percentage points in Bolivia. Yet in El Salvador, men are 2 percentage points more likely than women to face a high risk of automation. All these gender differences are statistically significant.

The paper is structured as follows. The second section provides a literature review, focusing on studies that analyze the gender dimension of automation. The third section describes the datasets and variables used in our analysis. The fourth section explains the methodology, while the fifth presents the results. The last section concludes.

2. What do we know about the gender dimension of the risk of automation?

The 4IR is characterized by the increased role of artificial intelligence, digitization, and robotics. As in other waves of industrialization, the 4IR is influencing the types of tasks individuals perform, which in turn affects the division of labor and the types of skills employers' demand (Autor and Handel, 2013). Yet how many jobs will be displaced by technology, and which workers will suffer the most?

The first studies to analyze the displacement effect of technology estimated the risk of automation and defined jobs at high risk as those with a 70% or higher probability of being displaced by technology. Frey and Osborne (2017) reported that 47% of US jobs were at a high risk of automation in the next 20 years. Pajarinen and Rouvinen (2014) report similar findings for Finland, Bowles (2014) for European countries, and Brzeski and Burk (2015) for Germany. Frey and Osborne's calculations generated a debate around a key assumption of the methodology – that automation affects entire occupations. However, occupations involve performing multiple tasks, not all of which are easy to automate. A task-based approach was developed based on Autor et al.'s (2003) prediction that technology automates tasks within occupations. Autor et al. (2003) developed a task-based model to predict the extent to which computerization can substitute for human labor. The model suggests that computerization *replaces* workers in limited and well-defined cognitive and manual activities that can be fulfilled by clear sets of rules (routine tasks) and *complements* workers in more complex problem-solving and communication activities (non-routine tasks). Calculations using this task-based approach predicted a smaller risk of automation than Frey and Osborne's (2017) occupation-based approach. Arntz et al. (2016) found that 9% of jobs were at high risk in OECD countries, and a similar percentage was estimated for the United States specifically.

Although several studies have obtained predictions of the risk of automation to future jobs, the gender dimension of automation has been largely overlooked. Our literature review focuses on

studies that use the task-based approach, which makes more realistic assumptions about the automatability of occupations.[1] Among these studies, OECD (2017) uses Arntz et al.'s (2016) estimates on a group of 29 OECD countries and predicts the risk of automation for men and women in different industries. They conclude that some large industries with high shares of women – such as food and beverage, service activities, and retail trade – have a high average risk of automation. However, men dominate in industries like manufacturing, construction and transportation, where the average risk of automation is also high. Summing across all industries, they find that the average risk of automation is similar for men and women.

Brussevich et al. (2018) use the PIAAC survey for a group of 30 countries (28 OECD countries plus Singapore and Cyprus) and show that women, on average, perform more of the tasks most prone to automation than men – i.e., routine tasks – across all sectors and occupations. As a result, they estimate that 11% of the female workforce is at a high risk of automation compared to 9% of the male workforce. Women with lower levels of education, those aged 40 and older, and those employed in low-skilled clerical, service, and sales positions are expected to be disproportionately affected by automation.

PwC (2018) uses similar data as Brussevich et al. (2018), but proposes different automation scenarios. The study calculates the gender gap in the risk of automation for a group of 29 countries (27 from OECD, Singapore and Russia) using the PIAAC survey. The authors find that women are expected to be at a higher risk than men up to the late 2020s, when they expect the technology to interact dynamically in clerical support jobs and decision-making processes and to have robots performing tasks in semi-controlled environments. However, by the late 2030s, when physical labor, manual dexterity and problem solving of real-world situations is expected to be automated, the study predicts that men will face a higher risk of automation (34%) than women (26%) because they are more likely to be employed in sectors that are intensive in manual tasks, while women tend to be concentrated in sectors such as education and health that entail less automatable skills.

[1] Studies with a gender dimension that apply the occupation-based approach find that 61% of women and 53% of men face a high risk of automation in the southeast region (Cambodia, Indonesia, Philippines, Thailand and Viet Nam) (Chang and Huynh, 2016), 58% of all jobs with a high risk of automation are held by women in the United States (Hegewisch et al., 2019), while women account for 54% of employment in high-risk occupations in Canada (Desjardins and Agopsowics, 2019).

White et al. (2019) focus their analysis on England. Combining data from the PIAAC survey and an annual population survey, they identify occupations at a high and low risk of automation and explore the share of different groups of workers in each type of job. They find that while women account for 70% of workers in high-risk jobs, they only represent 43% in jobs at a low risk of automation.

Roberts et al. (2019) analyze the UK labor market and combine calculations from Arntz et al. (2016) with the UK labor force survey. Their estimates indicate that more than twice as many women as men work in occupations with a high potential for automation (9% of women compared to 4% of men), while women hold 64% of the jobs at a high risk of becoming obsolete due to automation.

Other studies have applied methodologies other than the occupation- or task-based approaches. For instance, McKinsey (2019) developed a methodology that includes components capturing jobs lost and the creation of new jobs due to technology adoption. The model assumes that an occupation is automatable only after all the tasks involved are automatable. In that respect, the method is closer to the task-based approach than to the occupation-based approach. The analysis focuses on 53 countries, with an emphasis on ten core countries. The main results for the sample of ten countries show that 20% of women and 21% of men risk losing their jobs by 2030 in an intermediate automation scenario, i.e., the pace of the impacts of automation in terms of employment resembles that of past technological changes, such as the automation of agriculture and manufacturing.

Finally, Muro et al. (2019) based their analysis on McKinsey's (2019) estimates and report that male workers in the United States are more vulnerable to potential future automation than women: they estimate the average risk of automation as 43% for men and 40% for women. They explained their findings in the overrepresentation of men in production, transportation, and construction-installation occupations – job areas that have above-average projected automation exposure. By contrast, women comprise a large share of the labor force in occupations that are relatively safe from automation, such as health care, personal services, and education.

The effects of automation by gender appear to differ depending on the countries analyzed and the methodology used. Studies using Arntz et al.'s (2016) task-based approach generally find that women face a higher risk of automation than men. The differential impact of automation by gender

has not be assessed for the LAC region. We seek to fill this gap in the literature in order to help policymakers determine where (and how) to invest resources. Our findings will help elucidate the relationship between tasks, skills building, and gender differences and how these relate to automation and the future of work.

3. Data sources and variable definitions

We use data from two surveys that collected worker-level data on tasks performed at work and use of skills. The first is the PIAAC survey, which was administered by the OECD in Chile in 2014. The second is the STEP survey, which was conducted by the World Bank in Colombia and Bolivia in 2012 and in El Salvador in 2013.

The sampling of these two surveys varies slightly. STEP surveyed people living in urban areas, while PIAAC surveyed those living in urban and rural areas. To account for these differences, we follow Bustelo et al. (2019) and remove data collected from workers in typically non-urban industries such as mining and quarrying, agriculture, and forestry and fishery. We define our sample as employed women and men aged 18–60. Using this sample of workers in each country, we construct a set of task measures that differs from those used in previous studies calculating the risk of automation (Arntz et al., 2016; Nedelkoska and Quintini, 2018; Brussevich et al., 2018).[2] We exploit the rich information available in STEP and PIAAC to generate five task measures closely related to the 'skills of the future', i.e., those that are highly valued today and are expected to be in high demand in the future (Mateo-Berganza et al., 2019), and two task measures capturing activities that can be substituted by the 4IR technology. We follow Grundke et al. (2017) and Bustelo et al. (2019) when constructing the set of task measures. The first group, which is linked to the use of skills such as creativity, communication, teamwork, critical thinking, digital and quantitative skills, includes: (i) ICT digital, (ii) managerial and communication, (iii) readiness to learn and creative problem solving, (iv) self-organization, and (v) STEM quantitative. The second group, which we expect to be highly substitutable by technology, includes: (vi) marketing and accounting, and (vii) physical. Details on the exact variables used to generate each task measure

[2] For instance, Nedelkoska and Quintini (2018) focus on what Frey and Osborne (2017) identified as "engineering bottlenecks" and use a set of ten task variables from the PIAAC survey related to perception manipulation, creative intelligence, and social intelligence. Arntz et al. (2016) and Brussevich et al. (2018), however, use 30 task-related variables from the PIAAC without grouping them into categories.

appear in Appendix Table A1, which also shows the correspondence between variables in STEP and PIAAC.[3]

We construct the task measures following a standardization procedure as in Acemoglu and Autor (2011) and Bustelo et al. (2019), such that for the entire sample of workers in each country, each task measure has a mean of zero and a standard deviation of one. The standardization allows us to overcome the difficulty of having variables measured with different scales in PIAAC and STEP. In the PIAAC survey, the task-related variables are categorical, capturing the frequency of completing different tasks (measured on a scale from "never" to "everyday"). In the STEP survey, some of the task-related variables are categorical, like in the PIAAC, while others are binary, capturing whether the task is performed by the surveyed worker or not. We also use other variables capturing workers' characteristics, including years of education and age, which are both comparable between surveys.

Table 1 shows the final estimation sample, which comprises 1,433 workers in Bolivia, 2,679 in Chile, 1,446 in Colombia, and 1,044 in El Salvador.

4. Calculating the risk of automation at the worker level

In order to study how automation would affect female and male workers in LAC, we proceed by following Arntz et al. (2016) who map the occupation level automation risks of Frey and Osborne to the task and demographic level using individual-level data on tasks performed at work and workers' characteristics based on the PIAAC survey of OECD countries.

For the pool of four countries and for each country separately, we estimate a model of the automatability of each occupation using Frey and Osborne's calculations for the United States on the set of tasks each worker performs in her job and other workers' observable characteristics.[4] The estimations are obtained for men and women separately. The general idea is to map workers' data – using STEP and PIACC survey data – to Frey and Osborne's occupation risks to estimate

[3] Appendix Table A1 comes from Bustelo et al. (2019); we adjusted it to included physical tasks as an extra category that was not analyzed in Bustelo et al. (2019).

[4] We run separate regression models for men and women in order to capture the structural differences in the relationship between our key explanatory variables and automation risks. This is analogous to interacting all variables with the gender dummy.

the probability of automation, given the tasks workers perform and other characteristics. This procedure allows to predict an automation risk that could differ within the same occupation depending on the combination of tasks workers perform and on workers' characteristics.

In order to map the automatability of each occupation obtained by Frey and Osborne for the United States to the individual-level data in our sample, we use a crosswalk to match the SOC (Standard Occupational Classification at 6 digits level) codes for the United States to the ISCO (International Standard Classification of Occupations at 3 digits level) codes available in the STEP and PIAAC surveys. Because the classification of occupations in PIAAC and STEP is coarser than the U.S. classification used by Frey and Osborne, we were not able to obtain a perfect match for some of the occupations. As a result, some persons in PIAAC and STEP were matched to multiple automation risks.

The estimation model explains the risk of automation at the occupation level with the set of tasks each worker performs and individual level characteristics:

$$\mathrm{y}_{ij}^{g} = \sum_{n=1}^{N} \beta_n \mathrm{X}_{in}^{g} + \epsilon_{ij}^{g}, \tag{1}$$

where y is the risk of automation of the occupation in which worker i of gender g is employed and X_n are variables capturing the set of seven tasks measures for worker i of gender g, indicator variables of educational level, and indicator variables of age groups. N is the total number of explanatory variables included in the model. β_n represents the influence of each variable, task measure and worker characteristic on the automatability of each occupation, while j indicates the number of automation risk matches each worker had.

Where multiple automation risks are linked to the same worker, we create a weight calculated as the inverse of the number of multiple matches (duplication weight hereafter). We regress the risk of automation, y_{ij}, onto the task measures and other observable characteristics, X_{in}, creating a predicted value of automation risk at the individual level, $\hat{y}_i$.[5] Because the automation risk is restricted to range between 0% and 100%, we use a generalized linear model and weight by the product of the individual weights available in the STEP and PIAAC surveys and the duplication weight introduced above.

[5] To simplify the notation, we do not add the indicator g but it is understood that the procedure is applied separately for the samples of women and men.

We then apply the expectation maximization algorithm proposed by Ibrahim (1990), which reweights the duplication weights to maximize the most likely automation risk. The new weights are calculated by taking the predicted value of automation risk, $\hat{y}_i$, and subtracting the automation risk at the occupation level obtained by Frey and Osborne, y_i, then dividing it by the summation of all the duplicate automation value differences:

$$w_{id} = \frac{f(\hat{y}_i - y_{ij}|x_{in}, \beta_n)}{\sum f(\hat{y}_i - y_{ij}\,|x_{in}, \beta_n)} < 1 \qquad (2)$$

$f(.)$ in equation (2) represents the standard normal density. This entire process is repeated until the weights converge. Final automation probabilities are then assigned to each worker. The automation probability is an expected value obtained as the product of the final weights and the predicted value of the automation risk ($\hat{y}_i$). In order to test the sensibility of our results to this reweighting procedure, we also estimate model (1) using the initial set of weights, i.e., survey weights multiplied by the duplication weight.

Using the predicted probability of automation at the worker level, we calculate the average risk of automation and we define workers facing a high risk of automation as those who have a 70% or higher likelihood of being displaced by technology. In the next section, we discuss these results for female and male workers separately, for all four countries together, and for each country individually. We also compare the distributions of automation risk for female and male workers with those obtained using the occupation-based approach, and discuss the marginal effects of the task measures and other observable worker characteristics obtained after estimating model (1) with the final set of weights.

It is important to note three caveats in our methodology. First, since we are using the samples of employed women and men, our data may have endogenous selection into the labor market, especially among women.[6] Similarly, other endogeneity issues may be affecting our model, such as selection of workers into occupations depending on their educational level or age. As our model is a reduced form that intends to capture the skill composition in each occupation, we are not particularly concern about the endogeneity issues in our estimation strategy. Nevertheless, we

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[6] Women participate in the labor market less than men, and this is a not random decision. For instance, such decisions can be related to factors such as the number of children at home or local social norms about gender roles.

stress these limitations, especially in the interpretation of the coefficient magnitudes when discussing our results below. Second, our dependent variable is the risk of automation that Frey and Osborne (2017) obtained using the occupation-based approach. In their procedure, they had experts rate the automation likelihood of 70 occupations and used this information to train their method. Although we use a more realistic task-based approach, our methodology still depends on these experts' assessments, which may lead to an overestimation of the automation risk.[7] Finally, despite the development and growing use of advanced technologies, it may not be possible or cost effective for LAC firms to adopt them due to financial restrictions and low relative labor costs; the lack of a workforce with the needed skills to interact with the new technology may also play a role (Bosch et al., 2018). Moreover, technologies are expected to create new jobs that do not exist today and to have a positive impact on labor demand through a productivity effect (Acemoglu and Restrepo, 2018; Acemoglu and Restrepo, 2019). Calculations of the risk of automation do not consider these potential positive impacts on employment.

Despite these caveats, the task-based approach has three important advantages. First, instead of assuming that technology can displace entire occupations, it divides each occupation into a set of tasks. This improvement upon the occupation-based approach considers the likelihood that only certain tasks within an occupation are at risk of being automated. Second, the set of tasks associated with each occupation can differ between countries, for instance due to the skill level of the labor force in each country; the task-based approach can capture these differences. Third, the set of tasks can differ between workers in the same occupation, and the task-based approach is flexible enough to consider this variation when estimating the risk of automation. The last point is particularly relevant for studying gender differences in the impact of automation technologies.

5. Results

This section describes the results obtained applying the methodology introduced in the previous section. We start by presenting descriptive statistics on the variables we use as controls in model (1) for the estimation samples of men and women in the four LAC countries under analysis. Then, we discuss the predicted risk of automation for women and men and compare the distributions

[7] As Arntz et al. (2016) indicate in their study, experts tend to overestimate the potential of new technologies, especially for tasks involving flexibility, power of judgement and common sense.

obtained using the task-based approach with those obtained applying the occupation-based approach. Next, we present the calculations of the average risk of automation and the percentage of workers at a high risk of automation. We close with a discussion of the marginal effect of different worker-level characteristics including task measures, level of education and age.

a. Descriptive statistics

Table 2 reports the descriptive statistics calculated for the pooled LAC countries studied here. Statistics are calculated using the sample of women and men used in the estimation of model (1), and the variables are those included as controls (X_n). We follow previous studies and use a very parsimonious set of variables including age, educational level, and task measures (Brussevich et al., 2018; Nedelkoska and Quintini, 2018).[8]

Men outperform women in readiness to learn and creativity, management and communication, STEM-quantitative, ICT and physical tasks. The gender gaps are statistically significant in all cases and range between 0.35 standard deviations above the mean value in favor of men in STEM to 0.06 standard deviations in readiness to learn and creativity. The gender difference in self-organization, which is related to the flexibility to adapt to changes and absorb shocks, favors women: they are 0.03 standard deviations above the mean, while men are 0.025 below. The same is true for marketing and accounting, which captures routine tasks that involve accounting-related skills, such as reading financial documents and marketing tasks, but the difference is not statistically significant.

These gender gaps reveal that men perform four out of five of the tasks that are expected to complement new technologies, and women are in a better situation in only one of them, although the gender difference is small. Yet of the tasks that are expected to be replaced by technology, men

[8] Nedelkoska and Quintini (2018) and Brussevich et al. (2018) also control for numeracy and literacy test results. We do not include these skill measures in our model because they are only available for Chile. For Bolivia and Colombia, we have information on literacy skills, but not on numeracy, while for El Salvador we do not have any skill measure. The studies also include firm size and public employment indicator variables as controls. Although we have information on firm size, we could not homogenize the categories available in STEP and PIAAC so we decided not to include this variable, while public employment data is not available in El Salvador.

carry out more physical tasks, while women are more involved than their male counterparts in marketing and accounting tasks, although this difference is not statistically different from zero.

The distribution of female and male workers by educational level is very similar in our sample; 57% of women and 58% of men have 13 years of education or more. Men are slightly younger, with a larger share of workers in the 18–25 age group and a smaller share in the 41–60 group.

b. Distribution of the predicted risk of automation

Figure 1 presents the distribution of the risk of automation for the samples of women and men in Bolivia, Chile, Colombia and El Salvador. It compares the distribution obtained using the task-based approach described in the methodology section ($\hat{y}_i$) with the distribution using the occupation-based approach (y_i) as a robustness check. Using the task-based approach to analyze data on a group of OECD countries, Arntz et al. (2016) found a larger share of workers with medium values of risk of automation in comparison to the occupation-based approach. As expected, we find a similar pattern for the four LAC countries.

In the four countries analyzed, the distribution of the risk of automation using the task-based approach shows that few workers, men and women, are at either the bottom or top of the distribution, i.e., have a very low or very high predicted risk of automation. Most of them face a medium level of risk.[9] This is especially the case in Colombia and El Salvador, where the distributions are more concentrated around medium values – between 60% and 70% of automation risk – than in Bolivia and Chile.

The distributions using the occupation-based approach are bipolar in all cases; most workers have a very low or very high risk of automation. In all four countries and for both genders, the shares of workers with a high risk of automation (top of the distribution) are larger than the shares facing a low risk (bottom of the distribution). The bipolar distribution using the occupation-based approach resembles the one presented by Frey and Osborne (2017) for the United States, and the contrast between the distributions using the task-based versus the occupation-based approaches is in line with the evidence presented by Arntz et al. (2016), also for the United States. This

[9] We also plotted the histograms of the automation risk and the non-parametric estimation for both the task- and the occupation-based approaches and we found similar shapes. More importantly, the histograms behave similar to the non-parametric estimations at the tails of the distributions.

differential pattern between methods is explained by the variation of task structures within occupations, which the task-based approach considers, and the occupation-based approach ignores.

c. Average risk of automation and percentage of workers at high risk

Based on the distributions of the estimated risk of automation presented in Figure 1, we calculate the average risk for women and men and the percentage of workers facing a risk greater than 70%. These are the main results of the study.

Panel A of Table 3 presents the average risk of automation for women and men when grouping the sample of the four countries under analysis and in each country separately. For the group of four LAC countries, women on average have a nearly 2-percentage-point greater risk than men -- 60.2% vs. 58.4%, respectively; this difference is statistically significant. When analyzing the results at the country level, we find that the average automation risk surpasses 50% for both women and men in all countries. The average risk is larger for both genders in El Salvador, followed by Colombia. The next highest is Bolivia for women and Chile for men. The gender gap in the average risk of automation indicates that women face a higher average risk in all countries, with differences ranging from 7.6 percentage points in Bolivia to 0.2 percentage points in Chile; the difference is statistically significant only in Bolivia.

Table 4 disaggregates the estimation of the average risk of automation by worker and employment characteristics for the group of four LAC countries.[10] Both women and men demonstrate a pattern of declining average risk of automation with age. The average risk for young workers surpasses that of adults and middle-aged workers by almost 10 percentage points. For all age groups, women face a 2–3 percentage-point larger risk of automation than men of a similar age. Our findings that the risk of automation declines with age and that the gender gap favors men in all age cohorts are consistent with evidence gathered in developed countries (Brussevich et al., 2018). One possible explanation for the higher risk of automation for younger workers is the selection of less-educated people into the labor force in this age cohort when there is a high return on capital accumulation (Brussevich et al., 2018). The higher risk that women face regardless of their age may reflect a

[10] We focus on the aggregate results for the LAC region to ensure a large number of observations in each group defined by worker and employment characteristics. Results at the country level present similar patterns and are available upon request.

female employment structure with a large share of women in high-risk occupations in all age groups, or a situation in which women face a higher risk of automation even in lower-risk occupations due to the combination of tasks they perform (Nedelkoska and Quintini, 2018).

The average risk of automation presents a clear declining pattern with education as well, in accordance with the available evidence for developed countries (Arntz et al., 2016; Nedelkoska and Quintini, 2018). Less educated female and male workers, on average, have a 15-percentage-point higher risk of automation than highly educated workers. Men exhibit a 2-percentage-point lower average risk than women in both educational groups.

The disaggregation by occupation shows that for both men and women, the average risk of automation increases as we move from managerial-level occupations to elementary occupations.[11] This finding is in line with previous evidence and is explained by the type of tasks workers in each occupation perform (Nedelkoska and Quintini, 2018). For instance, managers and professional workers are expected to carry out more managerial and STEM-quantitative tasks, while craft and related trades workers and those in elementary occupations are expected to perform more physically demanding tasks. The gender gaps within each occupation show that women face a higher average risk of automation among managers, professionals and technicians, clerical support workers, services and sales workers, and craft and related trades workers. This gap is larger and around 4 percentage points among services and sales workers. The average risk is larger for men in elementary occupations.

Finally, for both men and women, we find that the average risk of automation is lower in the care sector (education, health, and domestic service) than in the manufacturing and services sectors. This result is consistent with those found for OECD countries (Nedelkoska and Quintini, 2018) and is explained by the higher intensity of the care sector in tasks that are difficult to automate, i.e., those requiring the use of social skills. Considering the distribution of employment by gender in the region, the lower risk of automation in the care sector favors women, 30% of whom are employed in the care sector, compared to 6% of men (ILO, 2019). The analysis of the gender gap within each sector shows that the average risk of automation is greater for women in all sectors, and the gaps are larger in the care and services sectors. The larger average risk of automation for

[11] Elementary occupations include cleaners and helpers, agricultural, forestry and fishery laborers, laborers in mining, construction, manufacturing and transport, food preparation assistants, street and related sales and service workers.

women in the care sector comes as no surprise, as the small fraction of men working in this sector probably perform management tasks.[12]

Panel B of Table 3 presents the percentage of workers at a high risk of automation (70% or higher). For the group of all four LAC countries, our findings indicate that 21.1% of women and 18.9% of men are at a high risk of automation; this difference is statistically significant.

Behind these average figures, however, there are differences between countries, which largely reflect the different composition of tasks in occupations between them. The country-level results show some heterogeneities at statistically significant levels in the scale of potential job losses. Women in Bolivia, Colombia and El Salvador have the greatest risk of losing their jobs to advancements in robotics or algorithms (around 29%), followed by Chile (21%). Among men, El Salvador and Colombia are most at risk (31% and 26%, respectively), followed by Chile (18%) and Bolivia (10%).

We find that more women are at a high risk of automation than men in Bolivia, Chile and Colombia. In El Salvador, however, more men are at high risk. All differences are statistically significant and range from 19 percentage points in Bolivia (larger percentage for women) to 2 percentage points in El Salvador (larger percentage for men). The larger percentage of men at high risk in El Salvador can be explained by the different combinations of tasks men and women perform there, and by how each task measure affects the probability of automation. We analyze the last point in the following sub-section.

Our analysis shows that the gender gaps in the average risk of automation are generally small. However, we find large gender differences in the share of workers at a high risk of automation. With the exception of El Salvador, these differences indicate that women are in a more vulnerable situation than men.

In order to test the sensibility of our results to the reweighting procedure applied using the EM algorithm, we re-estimate our models using the initial set of weights, i.e., the survey weights multiplied by the duplication weights. The results are very similar to the ones discussed in this

[12] Our data shows that for the group of four LAC countries, management occupations represent 3.8% of men's employment within the care sector, while the percentage for women is 2.4%. Moreover, men outperform women in management and communication tasks within the care sector.

section, both in magnitude and in terms of gender gaps patterns, showing a higher average risk of automation for women and larger share of women at high risk.[13]

d. Contributing factors to the risk of automation

Table 5 presents the marginal effects obtained after estimating model (1) with the final set of weights. The results are presented for women and men and for the pool of four LAC countries and each country separately.[14] With this analysis, we expect to obtain suggestive evidence of the direction of the relationships between the risk of automation and the control variables in order to interpret the main results presented above.[15]

The task measures that are linked to the skills of the future generally have a negative association with the risk of automation, which we interpret as suggestive evidence that these types of skills can protect workers from job displacement.

When looking at the pool of countries and focusing on the statistically significant effects, we find the largest estimates for the management and communication measure. The same happens at the country level, where this task measure has the largest negative marginal effects for both women and men. The descriptive statistics showed that management and communication have one of the largest gender gaps in favor of men, leading us to conclude that this task measure is contributing to the lower risk of automation obtained for the sample of male workers. This result is directly connected to the idea of a glass ceiling that prevents women in the LAC region from accessing hierarchical positions in which management and communication tasks are important. Very importantly, the marginal effect is larger for women for the pool of countries and for each country individually except for Colombia, meaning that improvements in the skills linked to management and communication tasks could be very beneficial for women in terms of reducing their automation risk.

Self-organization and ICT task measures have a negative and significant association with the risk of automation among men in the sample of four countries; men also perform more ICT tasks than

[13] These results are available upon request.
[14] The regression results are available in Appendix Table A2.
[15] As we cannot rule out the incidence of unobservable factors affecting the risk of automation and the task measures or workers' characteristics, the estimates need to be interpreted with caution.

women, which helps explain their lower risk of automation. Self-organization is more important among women according to our descriptive statistics, indicating that this task measure is not among the main factors explaining the lower automation risk for men. For the sample of women, readiness to learn and creativity are negatively associated with the risk of automation, but women perform fewer of these tasks compared to men.

Looking at the other task measures that are linked to the skills of the future for individual countries, there is a scattering of statistically significant marginal effects that are negative in most cases. We find negative and significant marginal effects of STEM-quantitative tasks for women and men in Bolivia, Chile and El Salvador, but not in Colombia or the pool of four countries. When significant, the magnitude of the effect is larger among women and for both men and women, the marginal effects of STEM-quantitative tasks are smaller in comparison to those of management of communication tasks.

Some exceptions to the pattern of a negative association between these tasks and the risk of automation are the positive and significant marginal effects of ICT tasks for men in Bolivia and women in El Salvador, and readiness to learn and creativity for men in El Salvador.[16]

As for the task measures that we expect to be substituted by 4IR technology, our findings show that whenever the marginal effects are statistically significant, the association with the automation risk is positive for both women and men. For marketing and accounting tasks, the marginal effect is larger among women who also perform more of these tasks, which helps explain their greater risk of automation. Yet the marginal effect for physical tasks is larger for men, who also perform these tasks more intensively. This last result mitigates the general finding of gender gaps in task measures and their marginal effects contributing to the larger risk of automation estimated for the sample of women.

Workers with higher levels of education have a lower risk of automation than those with lower levels of education in the samples of women and men. This result is in line with the evidence presented by Arntz et al. (2016), Brussevich et al. (2018) and Nedelkoska and Quintini (2018) for OECD countries. Finally, workers in the 26–40 and 41–60 age groups have a lower risk of

[16] We believe the positive association between readiness and creativity and the risk of automation for the sample of men in El Salvador can explain the larger percentage of men at high risk in this country, where we find that men perform more such tasks than women.

automation than younger workers. The marginal effects are statistically significant for women and men using the pool sample, and in some but not all country samples. The marginal effect increases with age. The negative association between the risk of automation and age is also in line with Brussevich et al. (2018) and Nedelkoska and Quintini (2018).

6. Final remarks

Digital transformation could worsen existing gender inequalities in the labor market, and it is pressing to take action to avoid this outcome. In this paper we assessed the level of risk that women and men in four LAC countries are likely to face due to automation. Our main findings indicate that men perform more of the tasks that are linked to the 'skills of the future' (i.e., STEM quantitative, ICT, management and communication) than women. As a result, women have a higher average risk of automation when grouping the four countries, and the share of women at a high risk is also larger: 21% of women vs. 19% of men face a high risk of automation. Using data on the number of employed women and men from the last available household surveys of Bolivia, Chile, Colombia and El Salvador, we found that the reported percentages translate into 3.4 millions of women and 4.2 millions of men being at risk of being displaced by technology. The magnitude is substantially higher for men because their labor force participation and employment rates are higher (BID, 2020).

What can be done to level the playing field for women? To answer this question, it is important to first understand what is behind the gender gaps we found in the tasks typically performed at work. The reported differences are directly related to two important characteristics of labor markets in the region. First, occupations are frequently segregated by gender. Men tend to be employed in sectors such as finance, construction and farming, where they perform STEM-quantitative, ICT digital and also physical tasks, while women are mainly employed in the care sector (education, health and domestic service), which requires tasks linked to the skills of the future, but where men perform more of these tasks according to our calculations. Second, women face barriers that restrict their access to hierarchical positions, where management and communication tasks are performed more intensively and according to our results, these are the type of tasks with the largest impact on the risk of automation.

To close these labor market gender gaps, we need policies that promote women's employability and career advancement in quality jobs, such as expanding the supply of care services to ease women's time restrictions, mentoring and support programs to facilitate women's access to contact networks and to help promote female role models, and increasing the provision of flexible work options for women and men.

Another underlying reason for the gender differences in tasks performed at work and in the risk of being displaced by technology is the small share of women acquiring the skills of the future, which allow workers to perform tasks such as STEM quantitative and ICT digital. For instance, only 3 out of 10 workers in the fields of mathematics and computer science in LAC are women (BID, 2019). According to our estimates, these tasks have the potential to reduce the automation risk in some of the countries analyzed, and especially among women in the case of STEM-quantitative tasks. Closing this educational gap requires investing in women's and girls' education in STEM fields with a quantitative and digital focus and promoting the upgrading of skills over their lifetimes.

In short, LAC countries must invest heavily in developing the right skills for girls who will enter the labor market in the future. Upgrading the skills of both women and men who are already in the labor force is equally important and represents an opportunity to close the labor gender gaps the region has been experiencing for a long time.

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Table 1. Sample size

	Women	Men	Total
Bolivia	776	657	1,433
Chile	1,446	1,233	2,679
Colombia	708	738	1,446
El Salvador	536	508	1,044
Four LAC Countries	3,466	3,136	6,602

Source: Authors' calculation based on the PIAAC (Chile, 2014) and STEP surveys (Bolivia, 2012; Colombia, 2012, El Salvador, 2013).
Notes: Sample of employed urban women and men aged 18–60. We excluded workers from the mining and quarrying, agriculture, and forestry and fishery sectors.

Table 2. Descriptive statistics: Averages for four LAC countries (Bolivia, Chile, Colombia and El Salvador)

	Women	Men	Mean diff. test
Tasks performed at work			
Marketing & Accounting	0.029	0.01	0.019
	[0.017]	[0.018]	[0.025]
Readiness to learn & Creativity	-0.034	0.03	-0.064***
	[0.017]	[0.018]	[0.025]
Management & Communication	-0.124	0.113	-0.237***
	[0.017]	[0.018]	[0.024]
Self-organization	0.033	-0.025	0.058**
	[0.017]	[0.017]	[0.025]
STEM quantitative	-0.164	0.183	-0.347***
	[0.015]	[0.019]	[0.024]
ICT	-0.115	0.11	-0.225***
	[0.017]	[0.018]	[0.024]
Physical	-0.096	0.097	-0.193***
	[0.016]	[0.016]	[0.023]
Level of education			
Low level of education (<=13)	42.787	42.411	0.376***
	[0.084]	[0.088]	[0.122]
High level of education (>13)	57.213	57.589	-0.376***
	[0.084]	[0.088]	[0.122]
Age groups			
Age group 18–25	14.368	16.709	-2.341***
	[0.060]	[0.067]	[0.089]
Age group 26–40	42.874	42.921	-0.047
	[0.084]	[0.088]	[0.122]
Age group 41–60	42.758	40.37	2.388***
	[0.084]	[0.088]	[0.121]
Observations	3,466	3,136	

Source: Authors' calculation based on the PIAAC (Chile, 2014) and STEP surveys (Bolivia, 2012; Colombia, 2012, El Salvador, 2013).
Notes: The table shows the descriptive statistics for the pool of four LAC countries under analysis. Standard errors between brackets. ** * Significant at 1%, ** 5% and * 10%. Sample of employed urban women and men aged 18–60. We excluded workers from the mining and quarrying, agriculture, and forestry and fishery sectors.

Table 3. Average risk of automation and share of workers at high risk

	Women	Men	Mean diff. test	Obs. Women	Obs. Men
Panel A: Average risk of automation					
Four LAC Countries	0.602	0.584	0.018***	3,466	3,136
	[0.002]	[0.002]	[0.003]		
Bolivia	0.599	0.523	0.076***	776	657
	[0.005]	[0.005]	[0.008]		
Chile	0.573	0.571	0.002	1,446	1,233
	[0.004]	[0.004]	[0.005]		
Colombia	0.637	0.63	0.007	708	738
	[0.004]	[0.004]	[0.005]		
El Salvador	0.643	0.639	0.004	536	508
	[0.004]	[0.005]	[0.006]		
Panel B: Proportion of workers with a high risk of automation (>70%)					
Four LAC Countries	21.148	18.909	2.239***	3,466	3,136
	[0.069]	[0.070]	[0.099]		
Bolivia	29.51	10.35	19.160***	776	657
	[0.164]	[0.119]	[0.202]		
Chile	21.024	18.086	2.938***	1,446	1,233
	[0.107]	[0.110]	[0.153]		
Colombia	29.237	25.881	3.357***	708	738
	[0.171]	[0.161]	[0.235]		
El Salvador	28.918	31.102	-2.184***	536	508
	[0.196]	[0.206]	[0.284]		

Source: Authors' calculation based on the PIAAC (Chile, 2014) and STEP surveys (Bolivia, 2012; Colombia, 2012, El Salvador, 2013).
Notes: Standard errors between brackets. ** * Significant at 1%, ** 5% and * 10%. Sample of employed urban women and men aged 18–60. We excluded workers from the mining and quarrying, agriculture, and forestry and fishery sectors.

Table 4. Average risk of automation for women and men by worker and employment characteristics: Averages for four LAC countries (Bolivia, Chile, Colombia and El Salvador)

	Women	Men	Mean diff. test	Obs. Women	Obs. Men
Age groups					
Young adults (18–25)	0.68	0.66	0.03***	497	522
	[0.004]	[0.005]	[0.006]		
Adulthood (26–40)	0.60	0.57	0.02***	1,484	1,342
	[0.003]	[0.003]	[0.004]		
Middle age (41–60)	0.58	0.56	0.02***	1,479	1,260
	[0.003]	[0.003]	[0.004]		
Education					
Low (<=13 years of education)	0.69	0.67	0.02***	1,481	1,322
	[0.002]	[0.002]	[0.003]		
High (>13 years of education)	0.54	0.52	0.017***	1,979	1,802
	[0.002]	[0.003]	[0.003]		
Occupation					
Managers, Professionals & Technicians and Associate Professionals	0.49	0.48	0.02***	807	819
	[0.003]	[0.004]	[0.005]		
Clerical Support Workers	0.58	0.55	0.02**	319	271
	[0.006]	[0.007]	[0.009]		
Services & Sales Workers	0.63	0.59	0.04***	1,253	526
	[0.003]	[0.004]	[0.005]		
Craft & Related Trades Workers and Plant & Machine Operators & Assemblers	0.64	0.63	0.01**	393	1,162
	[0.005]	[0.003]	[0.006]		
Elementary Occupations	0.66	0.70	-0.03***	688	346
	[0.003]	[0.005]	[0.006]		
Economic sector					
Care	0.57	0.52	0.04***	872	183
	[0.004]	[0.009]	[0.010]		
Manufacturing	0.62	0.60	0.02**	517	643
	[0.005]	[0.005]	[0.007]		
Services	0.63	0.59	0.04***	1,351	906
	[0.003]	[0.004]	[0.005]		

Source: Authors' calculation based on the PIAAC (Chile, 2014) and STEP surveys (Bolivia, 2012; Colombia, 2012, El Salvador, 2013).

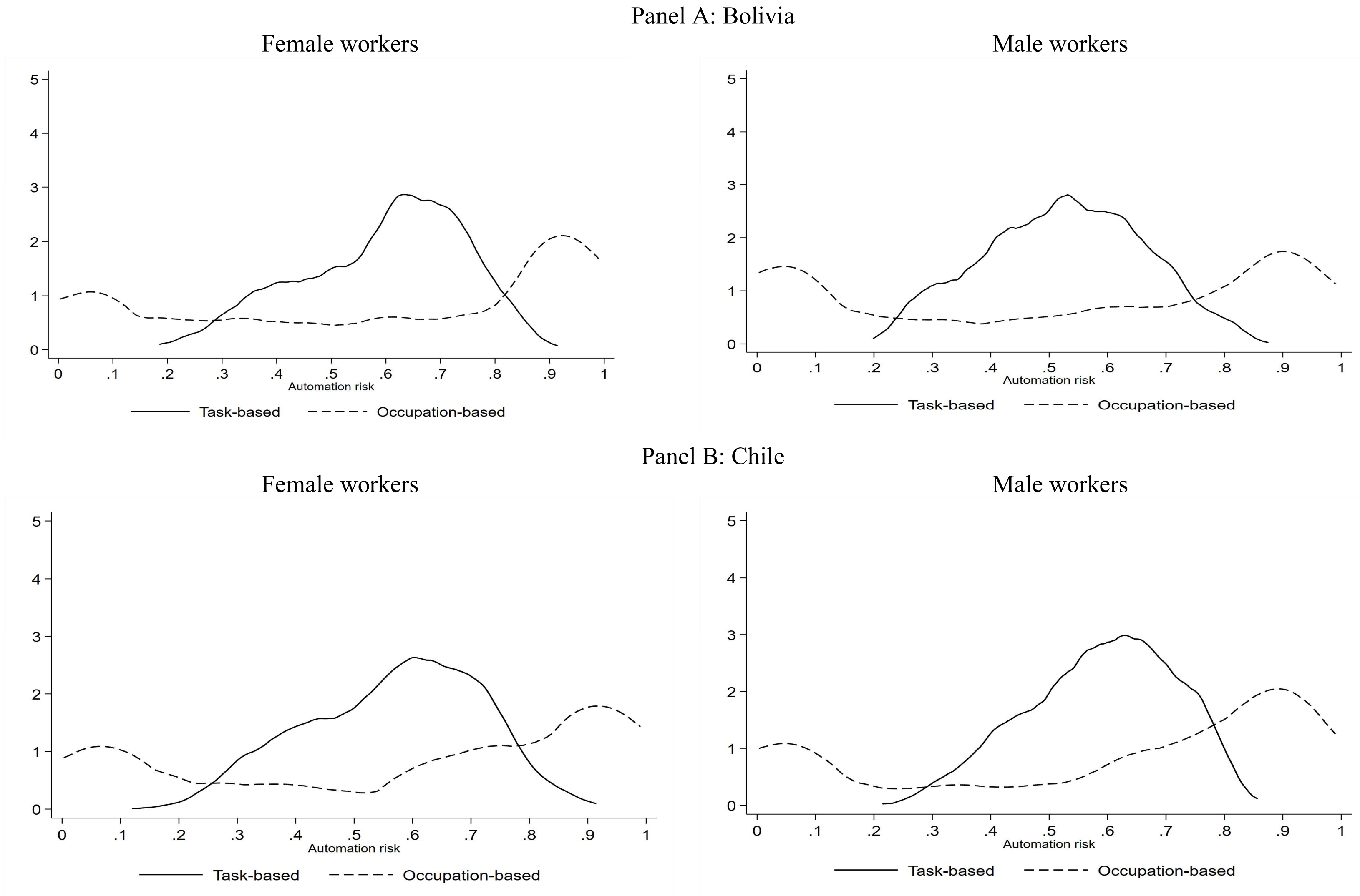
Notes: Standard errors between brackets. ** * Significant at 1%, ** 5% and * 10%. Sample of employed urban women and men aged 18–60. We excluded workers from the mining and quarrying, agriculture, and forestry and fishery sectors. Elementary occupations include cleaners and helpers, agricultural, forestry and fishery laborers, laborers in mining, construction, manufacturing and transport, food preparation assistants, street and related sales and service workers. Care sector includes health, education and domestic service.

Table 5. Risk of automation, task measures and workers' characteristics: Estimated marginal effects

	Four LAC Countries		Bolivia		Chile		Colombia		El Salvador	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Marketing & Accounting	0.005	0.056***	0.039***	0.069***	-0.005	0.096***	0.006	0.025*	0.030***	0.049***
	[0.009]	[0.008]	[0.010]	[0.009]	[0.016]	[0.015]	[0.011]	[0.011]	[0.005]	[0.005]
Readiness to learn & Creativity	-0.009	-0.016*	-0.018*	0.000	0.000	0.001	-0.021*	-0.037***	0.016***	-0.021***
	[0.008]	[0.008]	[0.009]	[0.010]	[0.013]	[0.015]	[0.010]	[0.010]	[0.004]	[0.005]
Management & Communication	-0.057***	-0.064***	-0.073***	-0.110***	-0.043**	-0.090***	-0.058***	-0.041***	-0.065***	-0.067***
	[0.009]	[0.009]	[0.010]	[0.011]	[0.015]	[0.014]	[0.010]	[0.012]	[0.006]	[0.006]
Self-organization	-0.021**	-0.011	-0.013	0.011	-0.018	-0.036*	-0.026**	0.005	-0.011*	-0.025***
	[0.008]	[0.009]	[0.009]	[0.009]	[0.013]	[0.014]	[0.009]	[0.009]	[0.004]	[0.005]
STEM quantitative	-0.016	-0.018	-0.027*	-0.047***	-0.038*	-0.042*	0.001	0.016	-0.015**	-0.019***
	[0.009]	[0.010]	[0.011]	[0.011]	[0.015]	[0.019]	[0.011]	[0.013]	[0.005]	[0.006]
ICT	-0.018*	-0.013	0.024*	0.018	-0.02	-0.052**	-0.013	0.001	-0.013*	0.030***
	[0.009]	[0.009]	[0.011]	[0.010]	[0.017]	[0.017]	[0.010]	[0.010]	[0.005]	[0.006]
Physical	0.039***	0.001	0.071***	0.029***	0.022	0.011	0.045***	-0.013	0.045**	-0.013*
	[0.008]	[0.008]	[0.008]	[0.009]	[0.013]	[0.013]	[0.010]	[0.011]	[0.017]	[0.006]
High level of education (>13)	-0.070***	-0.096***	-0.089***	-0.069**	-0.117***	-0.067*	-0.023	-0.117***	-0.067***	-0.045***
	[0.016]	[0.017]	[0.017]	[0.022]	[0.029]	[0.029]	[0.023]	[0.024]	[0.009]	[0.010]
Age group 26–40	-0.038*	-0.072***	-0.086***	-0.044	-0.047	-0.053	-0.016	-0.064*	-0.047***	-0.034**
	[0.017]	[0.021]	[0.023]	[0.027]	[0.039]	[0.044]	[0.022]	[0.028]	[0.011]	[0.013]
Age group 41–60	-0.069***	-0.110***	-0.025	-0.089**	-0.079*	-0.125**	-0.04	-0.095**	-0.091***	-0.081***
	[0.016]	[0.022]	[0.024]	[0.029]	[0.038]	[0.043]	[0.022]	[0.030]	[0.011]	[0.013]
Country FE	Yes	Yes	No	No	No	No	No	No	No	No
Number of observations	24,943	18,996	5,110	4,217	3,013	2,449	5,485	3,974	11,335	8,356

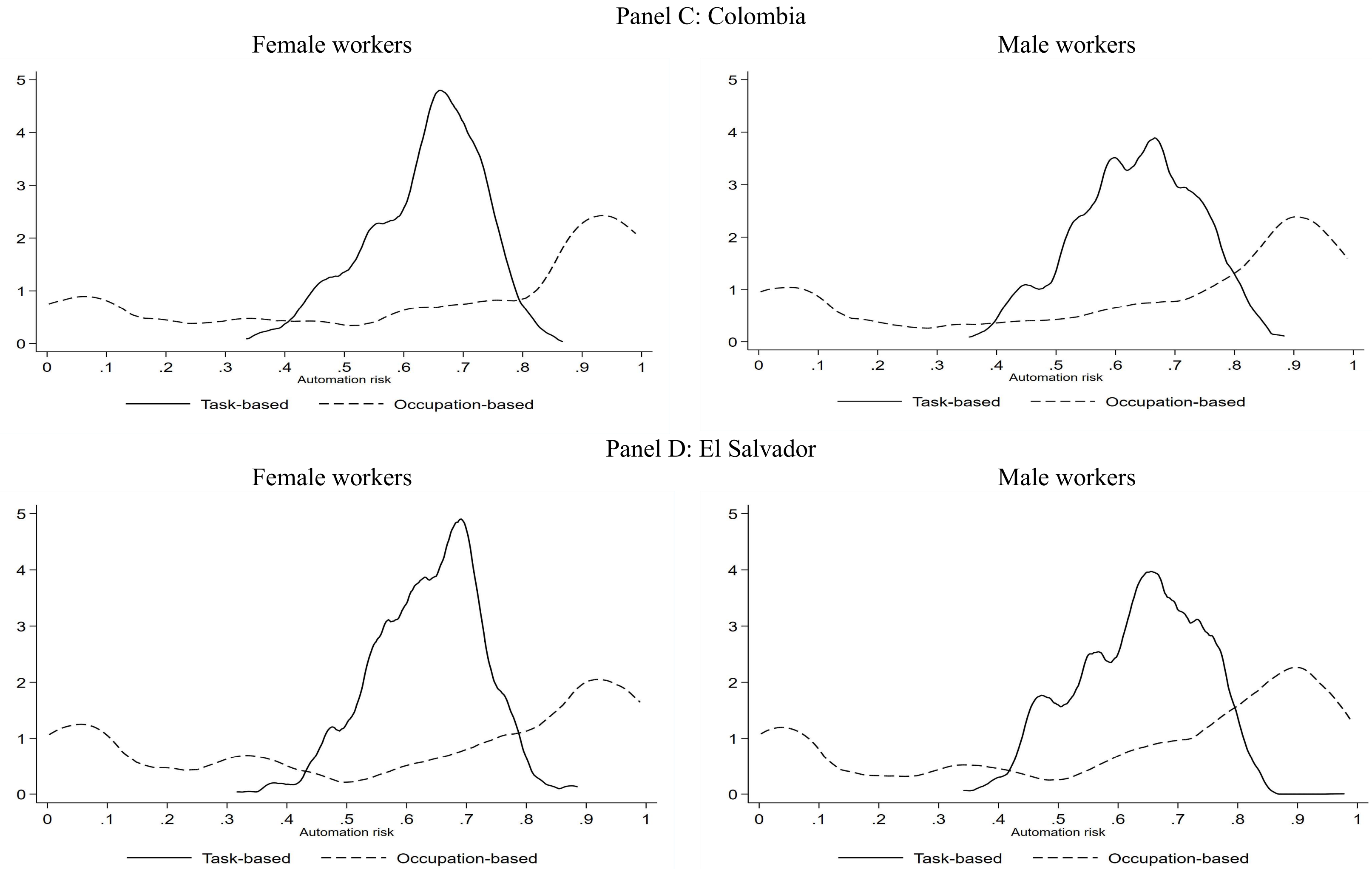
Source: Authors' calculation based on the PIAAC (Chile, 2014) and STEP surveys (Bolivia, 2012; Colombia, 2012, El Salvador, 2013).
Notes: Robust standard errors between brackets. The table shows the marginal effects obtained after estimating model (1) with the final set of weights. *** Significant at 1%, ** 5% and * 10%. Sample of employed urban women and men aged 18–60. We excluded workers from the mining and quarrying, agriculture, and forestry and fishery sectors.

Figure 1. Risk of automation: Task-based versus occupation-based approaches



Source: Authors' calculation based on PIAAC (Chile, 2014), STEP (Bolivia, 2012; Colombia, 2012, El Salvador, 2013), and Frey and Osborne's (2017) estimates.

Continuation Figure 1. Risk of automation: Task-based versus occupation-based approaches



Source: Authors' calculation based on PIAAC (Chile, 2014), STEP (Bolivia, 2012; Colombia, 2012, El Salvador, 2013), and Frey and Osborne's (2017) estimates.

Appendix

Table A1. Task-related questions from the PIAAC and STEP surveys

Task measure	PIAAC		STEP	
	Questions used	Metric	Questions used	Metric
ICT	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 computer	1 (never) to 5 (every day)	Do 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 designing websites	Yes/No
			Use of CAD software	Yes/No
			Use of statistical or other type of analysis	Yes/No
			Use of software programming	Yes/No
			Use of managing computer networks	Yes/No
Managerial and communication	Frequency of negotiating with people inside or outside the firm or organization	1 (never) to 5 (every day)	Contact with people other than co-workers, for example with customers, clients, students, or the public	Yes/No
	Frequency of planning activities of others	1 (never) to 5 (every day)	Meeting or interacting 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)		

Source: Taken from Table A1 in Bustelo et al. (2019). We added the category Physical tasks, which was not included in the cited paper.
Notes: *Reverse order* means we reversed the order of the categories such that a higher value indicates a higher frequency of tasks.

Table A1 continuation: Task-related questions from the PIAAC and STEP surveys

Task 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)	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 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, e.g. keep working when others stop to take a break	1 (almost always) to 4 (almost never); reverse order
			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 calculator	1 (never) to 5 (every day)		
	Frequency of selling a product or a service	1 (never) to 5 (every day)		
STEM quantitative	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
Physical	Frequency of working physically for long	1 (never) to 5 (every day)	Work is physically demanding	1 (not at all) to 10 (extremely demanding)

Source: Taken from Table A1 in Bustelo et al. (2019). We added the category Physical tasks, which was not included in the cited paper.
Notes: *Reverse order* means we reversed the order of the categories such that a higher value indicates a higher frequency of tasks.

Table A2. Estimation of the risk of automation

	Four LAC Countries		Bolivia		Chile		Colombia		El Salvador	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
Marketing & Accounting	0.015	0.154***	0.105***	0.193***	-0.013	0.265***	0.018	0.068*	0.083***	0.135***
	[0.024]	[0.023]	[0.028]	[0.026]	[0.043]	[0.042]	[0.029]	[0.030]	[0.014]	[0.013]
Readiness to learn & Creativity	-0.024	-0.045*	-0.048*	-0.001	0.000	0.002	-0.058*	-0.102***	0.045***	-0.059***
	[0.021]	[0.023]	[0.024]	[0.029]	[0.034]	[0.041]	[0.028]	[0.028]	[0.012]	[0.013]
Management & Communication	-0.157***	-0.174***	-0.196***	-0.309***	-0.117**	-0.249***	-0.161***	-0.114***	-0.180***	-0.185***
	[0.024]	[0.024]	[0.027]	[0.031]	[0.041]	[0.039]	[0.028]	[0.032]	[0.015]	[0.016]
Self-organization	-0.058**	-0.029	-0.036	0.03	-0.048	-0.099*	-0.072**	0.013	-0.031*	-0.068***
	[0.021]	[0.023]	[0.023]	[0.025]	[0.035]	[0.040]	[0.025]	[0.026]	[0.012]	[0.013]
STEM quantitative	-0.044	-0.048	-0.072*	-0.131***	-0.102*	-0.115*	0.004	0.044	-0.041**	-0.052***
	[0.024]	[0.028]	[0.030]	[0.031]	[0.042]	[0.054]	[0.030]	[0.036]	[0.013]	[0.015]
ICT	-0.049*	-0.035	0.065*	0.051	-0.055	-0.142**	-0.036	0.003	-0.035*	0.082***
	[0.025]	[0.024]	[0.030]	[0.028]	[0.047]	[0.048]	[0.027]	[0.028]	[0.014]	[0.015]
Physical skills	0.106***	0.003	0.192***	0.080***	0.06	0.03	0.126***	-0.037	0.124**	-0.035*
	[0.022]	[0.023]	[0.023]	[0.024]	[0.036]	[0.036]	[0.027]	[0.031]	[0.046]	[0.017]
High level of education (>13)	-0.191***	-0.260***	-0.238***	-0.192**	-0.318***	-0.185*	-0.063	-0.322***	-0.184***	-0.125***
	[0.043]	[0.047]	[0.047]	[0.062]	[0.080]	[0.081]	[0.063]	[0.067]	[0.025]	[0.029]
Age group 26–40	-0.106*	-0.203***	-0.230***	-0.126	-0.13	-0.153	-0.045	-0.183*	-0.132***	-0.098**
	[0.047]	[0.060]	[0.063]	[0.079]	[0.109]	[0.128]	[0.062]	[0.081]	[0.031]	[0.036]
Age group 41–60	-0.191***	-0.305***	-0.067	-0.249**	-0.216*	-0.348**	-0.11	-0.266**	-0.253***	-0.226***
	[0.045]	[0.062]	[0.064]	[0.083]	[0.105]	[0.124]	[0.061]	[0.086]	[0.032]	[0.038]
Constant	0.344***	0.573***	0.358***	0.463***	0.596***	0.503***	0.427***	0.641***	0.650***	0.536***
	[0.049]	[0.063]	[0.058]	[0.095]	[0.103]	[0.136]	[0.050]	[0.076]	[0.027]	[0.035]
Country FE	Yes	Yes	No	No	No	No	No	No	No	No
Number of observations	24,943	18,996	5,110	4,217	3,013	2,449	5,485	3,974	11,335	8,356

Source: Authors' calculation based on PIAAC (Chile, 2014), STEP (Bolivia, 2012; Colombia, 2012, El Salvador, 2013). Notes: The table shows the coefficients associated with the estimation of model (1) using the final set of weights. Robust standard errors between brackets. *** Significant at 1%, ** 5% and * 10%. Sample of employed urban women and men aged 18–60. We excluded workers from the mining and quarrying, agriculture, and forestry and fishery sectors.