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The Risk of Automation in Latin America [*]

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Abstract

In this paper we characterize workers' vulnerability to automation in the near future in the six largest Latin American economies as a function of the exposure to routinization of the tasks that they perform and the potential automation of their occupation. We combine (i) indicators of potential automatability by occupation and (ii) worker's information on occupation and other labor variables. We find that the ongoing process of automation is likely to significantly affect the structure of employment. In particular, unskilled and semi-skilled workers are likely to bear a disproportionate share of the adjustment costs. Automation will probably be a more dangerous threat for equality than for overall employment.

Keywords: jobs, employment, income distribution, automation, routinization, Latin America
JEL codes: J21, J23, J24, O33

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1. Introduction

Technological change is one of the main engines of economic growth and social progress. However, technical advances typically alter the production process and hence modify the productivity and ultimately the demand for different factors. Large changes in technology are profoundly disruptive, at least in the short run.

The concerns for the social and labor impacts of the technological changes are not new: the rebellion of the *luddites* against the machines of the Industrial Revolution, and the worries of J.M. Keynes about the technological unemployment are just examples of the fears raised by technical innovations. These fears, however, proved to be largely misplaced: although in the short run machines did displace workers, productivity increased and new jobs were created, so that in the long run economic growth was strongly boosted by new technologies and unemployment did not significantly increase.

A new wave of strong technological advances are under way. Automation and digitalization are the new technologies that boost productivity, growth, and wealth, but also disrupt labor market's structure. The major concern is that new technologies may displace a significant share of workers out of the labor market. Will this time be different? Some argue that the nature of the new technological innovations places a much stronger threat on employment than previous "industrial revolutions". But even if overall employment is not significantly affected, it is likely that the new technologies modify the relative demands for different types of workers, affecting the structure of employment and ultimately the income distribution.

The main goal of this paper is to characterize workers' vulnerability to automation in the near future in Latin America as a function of the exposure to routinization of the tasks they perform and the potential robotization of their occupation. In order to do that we combine two different sets of data: (i) indicators of potential automatability by occupation and (ii) worker's information on occupation and other labor variables.

We rely on two different measures of risk of future automation recently developed by Frey and Osborne (2017) and Arntz *et al*. (2016, 2020). These indicators of risk of automation by occupation are combined with microdata on workers drawn from national household surveys. In particular, we use harmonized microdata from our own SEDLAC database (a joint collaboration between CEDLAS-UNLP and the World Bank) for the six largest Latin American economies - Argentina, Brazil, Chile, Colombia, Mexico and Peru, which represent 79% of total population and 86% of total GDP of the region. This large sample allows us to provide a global perspective of the future of jobs in Latin America.

According to our preferred estimates, we find that the ongoing process of automation is not likely to make a large dent on the overall rate of employment in Latin America. Instead, it is more likely for the expected technological changes to significantly affect the *structure* of employment. In particular, unskilled and semi-skilled workers are likely to bear a disproportionate share of the adjustment costs, since the automatability of their occupations is higher compared to skilled workers. Therefore, automation will probably be a more dangerous threat for equality than for overall employment.

The rest of this paper is organized as follows. In section 2 we review the literature on automatability. In section 3 we provide details on the methodology applied and the data used to estimate the risk of automation in the Latin American economies. The main results are presented in section 4. The paper closes in section 5 with some remarks.

2. Literature review

The early literature on skill-biased technological change dates back to the works of Katz and Murphy (1992), Bound and Johnson (1992) and Card and Lemieux (2001). Following the Tinbergen's idea of the race between technology and education this literature assumes that technology is complementary with skilled labor, therefore positively affecting the relative demand and wage of skilled workers. Technological change is thus associated to an unambiguous unequalizing effect on the income distribution.

More recently, with the proliferation of automation processes in the form of digital technology and robotics, the literature that studies technology and labor markets has shifted to the task-based approach of Autor *et al*. (2003) and Acemoglu and Autor (2011). The task approach argues that the complementarity or substitutability between technology and labor does not occur at the worker category level but rather depending on how susceptible different tasks are for automation. In particular, routine tasks that follow well-defined rules can be more easily automated based on rule-based algorithms, using increasingly powerful computers. As a consequence, labor demand for routine tasks has declined. Since routine tasks are more widespread among middle-skilled, medium-wage workers, automation has led to a polarization of the labor market with declining shares of middle-wage workers. A growing literature for developed countries documents that recent technological change replaces labor routine tasks that are heavily concentrated in the middle of the skills distribution. This hypothesis is known as *job polarization* (Autor and Dorn, 2013; Goos *et al*., 2014). The evidence for the developing world is much weaker. In fact, in a companion paper we find that the increase in jobs in Latin America was decreasing in the automatability of the tasks typically performed in each occupation, and increasing in the initial wage, a pattern more consistent with the traditional skill-biased technological change than with the polarization hypothesis (Gasparini *et al*., 2020).

Whereas the main objective of that line of research is to assess the impact of automation in the past decades, a recent strand takes a more prospective view, motivated by the acceleration in the implementation of new technologies. How many tasks or occupations might be automatable in the near future? What could be the effect on the labor market and on the income distribution? There have been a number of initiatives to estimate the capability of substituting occupations with machines in the near future. Naturally, the exercises are highly conjectural, as they imply predicting the spreading of recent technologies and the implementation of new ones. However, given the relevance of the potential economic and social impact of those changes, a new literature that estimates the risk of automation and the potential threat to jobs has recently emerged. The critical component of this body of research is how to define a job as "automatable".

So far, the most popular approach follows the study of Frey and Osborne (2017) (FO thereafter). Their empirical analysis proceeds in two steps. First, they use the 2010 version of O*NET, a database of information on the task content of 903 occupations in the US, constructed from the assessments of labor market analysts, experts and workers. The O*NET data is matched to the 702 occupations of the Labor Department's Standard Occupational Classification (SOC). Second, they assign to each occupation a probability of automation. In order to do that, they asked machine learning researchers to classify occupations into being either automatable or not, based on the reported task content.[1] In particular, they select 70 occupations whose labelling the experts were highly confident about, and then they impute the automatability to the remaining occupations based on a model of occupation's automatability on some attributes (*e.g.* manual dexterity, originality, social perceptiveness). The model returns an estimate of the automation potential: the likelihood that an occupation is technically automatable or, "strictly speaking, it is an estimate of the probability that the experts would have classified a given occupation as automatable during the workshop" (Arntz *et al.*, 2020). For simplicity FO divide occupations into three groups according to the probability of automation: low-risk (less than 30%), medium-risk (30-70%) and high-risk (>70%) occupations. They report that 47% of all jobs in the US are in the high-risk category.[2] Service, sales and office jobs are over-represented in that category. The risk of automation is higher for low-skilled workers and for low-wage occupations, suggesting that automation could disproportionately affect these groups of workers. Several authors have replicated the FO analysis in other countries, assuming that the automatability by occupation is the same as in the US.[3] Santos *et al.* (2015) apply this approach to ten developing countries and a Chinese province. They include a simple adjustment for the fact that technologies are adopted and diffused with a time lag in the developing world. In World Bank (2016) this methodology is extended to a larger sample of developing countries, including some, mostly small, Latin American countries: Nicaragua, Bolivia, Dominican R., Paraguay, El Salvador, Guatemala, Panama, Costar Rica, Ecuador, Uruguay and Argentina. Bosch *et al.* (2018) also estimate the risk of automation in a similar sample. They find that the proportion of workers in the high-risk group ranges from 62% in Dominican

[1] The specific question asked was: "*Can the tasks of this job be sufficiently specified, conditional on the availability of big data, to be performed by state of the art computer-controlled equipment*?"

[2] These occupations "are potentially automatable over some unspecified number of years, maybe a decade or two" (Frey and Osborne, 2017).

[3] Lawrence *et al.* (2017) for England, Brzeski and Burk (2015) for Germany, Pajarinen and Rouvinen (2014) for Finland, Bowles (2014) and PWC (2018) for a group of European Countries.

Republic to 75% in Guatemala: substantially higher than the estimate of 47% in the US. Weller *et al.* (2019) estimate an average risk of 62% for Latin America. They also consider the hypothesis that the ongoing technological change will not affect the informal sector. In that case, the mean risk of automation, using the FO methodology, falls to 24%.

Other authors have followed the FO approach but using different sources to assess the automation probabilities. Vermeulen *et al.* (2018) construct an expert assessment with inputs from roboticists, whereas Manyika *et al.* (2017) use a machine-learning algorithm to score the more than 2,000 work activities in relation to 18 performance capabilities. Josten and Lordan (2019) introduce an alternative classification of automatable occupations based on patent data from *Google Patents*. They argue that patents activity is a better proxy to identify the jobs that will be automatable in the near future. The authors take the non-automatable jobs defined by Autor and Dorn (2013) and assess the chances of becoming automatable in the near future based on patent activity in the area. Josten and Lordan (2019) find that 47% of all current jobs in the US are automatable over the next decade, an estimate similar to that of FO. The authors stress that the jobs with less risk of automation are those that involve abstract, strategic or creative thinking, with high interactions with people.

The FO approach assumes that occupations are homogeneous in terms of tasks. This is however a strong assumption, since workers of the same occupation usually conduct different tasks, and thus may be differently exposed to automation depending on the tasks performed (Autor and Handel, 2013).[4] In reaction to this concern, Arntz *et al.* (2016, 2017) follow a task-based instead of an occupation-based approach, by focusing on what people actually do in their jobs rather than relying on occupational descriptions of jobs. Information on tasks is obtained from the Programme for the International Assessment of Adult Competencies (PIAAC), a unique dataset which contains micro-level indicators on socio-economic characteristics, skills, job-related information, job-tasks and competencies for a sample of countries.

Based on US observations in the PIAAC, Arntz *et al.* (2017) estimate a model of the automatability indicator of FO on workers' actual tasks, and use

[4] In fact, the evidence suggests that the recent decline in routine tasks was driven by declining shares of routine tasks within occupations instead of declining shares of routine occupations (Spitz-Oener, 2006).

the predictions of this model as indicator of true automatability. A worker may have an occupation whose job description led FO to classify it as highly automatable, but if the actual tasks performed by the worker in that occupation (as reported to the PIAAC) imply less routine activities, the predicted automatability from the model will be lower. Following this approach Arntz *et al.* (2016) find that the threat to jobs is much less severe than estimated by other studies. While Frey and Osborne (2017) estimate that 47 percent of all U.S. workers are subject to a high risk of their jobs being automated over the next two decades, Arntz *et al.* (2017) reduce this estimate to 9 percent. The difference stems from the large variation of workers' tasks within occupations. In particular, many seemingly automatable jobs also include tasks for which machines are not well suited, such as problem solving or influencing decision making. Recently, other authors have applied variants of this task-based approach and found results in line to those of Arntz *et al.* (2016).[5]

3. Data and methodology

Our analysis combines workers' characteristics drawn from national household surveys in Latin America with some of the automatability (or "risk of automation") indicators described above, defined at the occupation level.

Indicators of risk of automation

We consider two alternative indicators of risk of automation, proposed by Arntz *et al.* (2016, 2020) (Alternative 1) and by Frey and Osborne (2017) (Alternative 2). Although they imply very different estimations for the overall degree of automatability, they are conceptually similar and they are highly correlated across occupations.

In Alternative 1 we make use of the automatability estimations of Arntz *et al.* (2016, 2020).[6] Following the methodology described in the previous section, they compute in 20 OECD countries an automatability occupation

[5] Nedelkoska and Quintini (2018) use PIAAC and find that 10% of U.S. workers are in the "high-risk" group. Pouliakas (2018) uses the European Skills and Jobs Survey (ESJS), and finds that 14% of workers in the European Union work in automatable jobs.

[6] We are very grateful to the authors for the data provided.

index that reflects the share of workers in that occupation with high automation potential (higher than 70%). The information is available at the ISCO-08 2-digit level. We take a weighted average of these indexes across countries, using the number of workers in each occupation as weights.[7] The main assumption is that this average is representative of the risk of automation in Latin America. This assumption may not be strong if technologies spread globally (even if they do it with lags) and if the structure of tasks by occupations are similar across countries. A comforting observation is that the characteristics and tasks by occupation reported in the PIAAC survey do not differ much among countries (Arntz, *et al*. 2017; Brambilla *et al*., 2021).

According to this task-based index there is substantial heterogeneity in the degree of automatability across occupations (Figure 1). Whereas the risk of automation in the near future is negligible for teaching, health, information and communication professionals, the risk is high for clerks, machine operators, sales workers, drivers, construction workers, and food preparation assistants. Around 30% of the jobs in these groups are severely threatened of being replaced by machines.

Our second risk-of-automation index is adapted from Frey and Osborne (2017). We match the 702 occupations of the Labor Department's Standard Occupational Classification (SOC) to the ISCO-08 two-digit classification using a crosswalk provided by the Bureau of Labor Statistics. Table 1 shows the risk of automation under this alternative (labeled as A2) in comparison with the previous one (labeled as A1). As discussed above, the risk of automation is higher under this approach. However, the correlation across occupations between the two alternative indices is high: the Pearson correlation is 0.707, and the Spearman rank correlation is 0.796, both highly statistically significant.

It is important to point out that these two automatability indicators refer to what theoretically could be automated in the future, given the

[7] The dataset for OECD countries has very few observations for the following occupations: Market-oriented Skilled Forestry; Fishery and Hunting Workers; Subsistence Farmers, Fishers, Hunters and Gatherers; Agricultural, Forestry and Fishery Labourers. We set the index of these sectors similar to the Market-oriented Skilled Agricultural Workers. Also, there were no observations for Street and Related Sales and Services Workers, so we assigned to them the mean index of related occupations: Personal Services Workers, Sales Workers, Food Preparation Assistants, Refuse Workers and Other Elementary Workers.

projections about the technology. This must not be equated with job-losses. The fact that automation is technically feasible for a task performed by some workers does not necessarily imply that all of these workers will actually be replaced by automated devices. The decision to utilize automation technologies or workers is ultimately based on economic considerations (Bosch *et al.*, 2018).[8]

National household surveys

In order to explore the labor market implications of the future risks of automation we rely on microdata from the official national household surveys of the six Latin America countries included in the study: Encuesta Permanente de Hogares (EPH) in Argentina, Pesquisa Nacional por Amostra de Domicilios Contínua (PNAD) in Brazil, Encuesta de Caracterización Socioeconómica Nacional (CASEN) in Chile, Gran Encuesta Integrada de Hogares (GEIH) in Colombia, Encuesta Nacional de Ingresos y Gastos de los Hogares (ENIGH) in Mexico, and Encuesta Nacional de Hogares (ENAHO) in Peru. Surveys were processed following the protocol of the Socioeconomic Database for Latin America and the Caribbean (SEDLAC), a joint project between CEDLAS at the Universidad Nacional de La Plata and the World Bank. Household surveys are not uniform across Latin American countries and in most cases not even within a country over time. The issue of comparability is of a great concern. Owing to that situation, we make all possible efforts to make statistics comparable across countries by using similar definitions of variables in each country and by applying consistent methods of processing the data (SEDLAC, 2020).

We carry out the analysis based on the latest available national household surveys in the six countries of our sample. In order to gain power, whenever possible we consider a window that includes years 2016, 2017 and 2018. Table 2 provides details on the information considered in each country. Overall, we use data on more than 2 million workers in the six largest economies of the region.

[8] As discussed in Arntz *et al*. (2020) there are three reasons that may disconnect the risk of automation from actual employment losses. "First, the utilization of new technologies is a slow process, due to economic, legal and societal hurdles, so that technological substitution often does not take place as expected. Second, even if new technologies are introduced, workers can adjust to changing technological endowments by switching tasks, thus preventing technological unemployment. Third, technological change also generates additional jobs through demand for new technologies and through higher competitiveness."

Unfortunately, Latin American countries do not use a common system of occupation codes. Countries use different versions of the ISCO classification or even their own codes. In order to have a unique classification, we convert the occupation codes of each country to the two-digit ISCO-08 classification using official crosswalks. Table 3 provides more information on this harmonization process.

4. Results

Given the occupation structure of workers in the six largest Latin American economies, the overall risk of automation is 16.7% under alternative 1 (Table 4). This value is higher than the OECD mean computed in Arntz *et al.* (2016) (9% of automatable jobs). In fact, the minimum value in our sample (15.4% in Chile) is higher than the maximum in the OECD countries (12% in Austria). This gap with the industrialized economies is driven by an occupation structure in Latin America biased towards low and middle-skill jobs, more vulnerable to the threat of automation in the near future.

Although there is some heterogeneity across countries in Latin America, the differences are not large. The proportion of jobs with high risk of automation ranges from 15.4% in Chile to 18.4% in Mexico. Differences are somewhat larger although still not sizeable across sub-national regions: from 11% in the rural areas of Peru to more than 18% in the Center and North of Mexico (Table 5 and Figure 2).

The overall risk of automation is on average 62% under alternative 2. The values for all Latin American countries in our sample are significantly higher than the index reported for the US by Frey and Osborne (2017) (47%).

The large differences with the estimates from alternative 1 are driven by the reasons already discussed in the previous section. In any case, all the estimations are highly speculative. In fact, it is more relevant to analyze the structure of the jobs at risk than the mean probability of automation.

Table 6 shows the proportion of jobs with high risk of automation by sector. The threat of automatability is higher in Commerce, Restaurants and Hotels, Transportation, Communications and Domestic Services, and lower in

Teaching, Health and Social Services. However, there is high variability within industries, as production in each sector requires a wide range of occupations.

According to the occupation structure in the six largest Latin American economies, the risk of automation is just slightly higher for male (16.8%) than for female (16.5%) workers (Table 7 and Figure 3). This narrow gender gap also holds under A2 (63.3% for males and 60.2% for women). Interestingly, whereas the risk of automation is higher for young men than for young women, the gap is reversed for older workers. For instance, the mean risk of automation for workers aged 18 to 35 is 18.0% for men and 17.1% for women; while for older workers aged 55 to 75 the risks become 15.6% for men and 17.2% for women.

The risk of automation is higher for very young workers. The proportion of jobs at risk falls with age until around 30. From that point on it increases but at a very slow pace (Figure 3). In fact, the risk of automation for workers in their 60s (16.3%) is just marginally larger than for their counterparts in their 30s (16.0%). This pattern also holds when using A2 to define automatability. According to these results, the prospect of automation poses a special threat on the jobs of young workers. This fact adds to the concerns on the job perspectives of youngsters, a group with the highest unemployment rates in the region.

Despite the much-commented increase in the perspectives of computerization in some high-skill occupations, the risk of automation is still considerably higher in low and medium-skilled jobs that involve routine-intense tasks. Figure 4 shows the results for the six largest Latin American economies. The proportion of jobs with high risk of automation is high for those with less than complete secondary education. More than a third of workers in Latin America are in this low-skill group, for which the risk of automation is around 18%. Automation risk peaks at 11 years of education. From that point on automatability dramatically falls with years of education. For those in the high-skill group, with 17 or more years of formal education, the risk of automation is just around 3%. The dramatic fall in automatability for high-skill workers is similar when using alternative A2, and also consistent with patterns found elsewhere (Arntz *et al*. 2016).

Interestingly, Figure 4 suggests that under Alternative 1 semi-skilled workers would be the group most affected by the ongoing process of automation. The risk of automation is also high for the unskilled (18.4%) but somewhat lower than for the semiskilled (19.5%).[9] The risk plummets for the skilled (9.4%). This pattern resembles the polarization story found in developed economies by Autor and Dorn (2013), Goos *et al*. (2014), and Autor (2019) among others: recent technological change replaces labor routine tasks that are more heavily concentrated in the middle of the skills distribution. In a companion paper we do not find evidence that Latin America experienced such a pattern in the past: Figure 4 suggests that it might happen in the future, given the new perspectives for automation. The evidence for polarization is, however, not conclusive. In fact, under alternative 2 the risk of automation is always decreasing in years of education. The difference with alternative 1 may be driven by low-skill occupations that although in general could be automated, they include some tasks more difficult to be performed by machines. These tasks, considered in alternative 1, are ignored by the FO methodology in alternative 2.

The mostly decreasing pattern of risk of automation on labor income is not surprising given the results by skills (Figure 5). The threat is high and just slightly increasing in the first three deciles of the earnings distribution: it goes from 18.7% in the bottom decile to 19.1% in decile 3; then it goes down slowly and then accelerates its fall from around percentile 70 on. The results are similar when using the hourly wage rather than the earnings distribution. When considering alternative 2 the pattern is monotonically decreasing on labor income.

Figure 6 shows automatability as a function of monthly earnings and hourly wages (not percentiles). The graph is a non-parametric estimation of the relationship between the risk of automation (under alternative 1) and earnings (or hourly wages), using locally weighted scatterplot smoothing (*lowess*) in the pool of Latin American countries. The risk of automation in the region is first slightly increasing in labor income and then strongly falls in the upper-tail of the earnings (wage) distribution.

Under alternative 1 the pattern of automatability shows an inverted U shape when considering a measure of household rather than worker income

[9] Semi-skilled are defined as those workers with 9 to 13 years of education. The rest of the groups are defined accordingly.

(Figure 7). While the risk of automation is around 17% in the bottom decile of the household income distribution, it climbs to 19.3% in decile 5 and then falls to 9.7% in the top decile. Under alternative 2 the pattern is monotonically decreasing: from 72.3% in the bottom decile to 43.2% in the top decile. In sum, although specific results vary across the alternative methodologies and income distributions, the main pattern remains: the risk of automation is higher for workers in the bottom and middle sections of the skill, earnings and income distributions.

Impact on income inequality

Assessing the impact of the risks of automation on the income distribution is a highly speculative endeavor. Even if we could estimate which workers are more likely to be directly affected by automation, it is almost impossible to estimate the general-equilibrium effects of such a major shock on the economy. Workers replaced by machines could become unemployed, or find a job in the same firm by performing a different task, or end up employed in other sector of the economy. And of course the implications could extend beyond workers initially reached by the introduction of robots and computers: the whole labor market will be affected in ways that are difficult to predict.

In this section we carry out two very simple, yet illustrative exercises. First, we compute changes in the labor income distribution assuming a proportional fall in earnings only for those workers initially affected by automation. Second, we estimate changes in the household per capita income distribution arising from the combined effect of two sources: (i) change in earnings according to the previous exercise and (ii) change in capital income after the replacement of workers by machines.

The first exercise is extremely simple. We focus on the initial partial-equilibrium effect of the technological change and assume that only earnings of workers directly affected by automation are modified. In addition, for simplicity we assume that the earnings fall is similar (in proportional terms) for all affected workers. Therefore, the wage after automation is equal to a factor β of the wage before automation. What would be the increase in earnings inequality in that simple scenario? Table 8 shows the Gini coefficient for alternative values of β.[10] For instance, the original Gini (β=1) for the period 2016-2018 in Argentina is 40.6. A reduction of 25% in wages of workers affected directly by automation (β=0.75) would increase the Gini coefficient to 41.4 (a 2% increase in inequality). Instead, if the fall is 50%, the Gini would rise to 43.1 (a 6% increase in inequality), whereas if automation drives workers to permanent unemployment (i.e. setting β=0), the Gini would dramatically increase to 50.2 (a 24% increase). The magnitude of the changes are similar in the rest of the Latin American countries.

The second exercise adds the likely increase in capital income due to automation. We assume that the introduction of robots implies an increase in capital income by the amount of the wages of the displaced workers. We also consider an alternative where the increase in capital income is just 50% of the saved wages.[11] We consider three alternatives in order to assign those rents: (i) to the top percentile of the household per capita income distribution (as proposed by Koru (2019)), (ii) proportional to capital income, and (iii) proportional to household per capita income. Table 9 shows the results. The mean original Gini coefficient for the household per capita income distribution in the six largest Latin American economies is 45.6. If for instance automation reduces earnings of affected workers by 25% while the capital incomes from automation go to the top percentile, then the Gini coefficient will increase to 53.3: a substantial jump in inequality of almost 8 Gini points (17%). The increase is even larger if rents are distributed as the current distribution of capital income: the Gini will rise almost 10 points to 55.3. The increase is smaller, although still economically relevant, if rents are just 50% of the replaced wages, or if rents are distributed as the current total income distribution. In contrast, the inequality increase would be larger if we assume that rents go only to skilled or non-routine workers.[12] The general conclusion from the results in Table 9 is that at least the direct partial-equilibrium effect

[10] To compute the results of the table we proceed as follows. Suppose the probability of automation of a given job j is p_j and that a given person i working in that job has a sample weight in the survey of m_i. Then, we assume that $p_j.m_i$ workers similar to i are fully affected by automation while $(1-p_j).m_i$ workers similar to i are not affected at all.

[11] Notice that the amount of these rents may be independent of the reduction in earnings for the displaced workers. For instance, capitalists could obtain rents by the same amount of the replaced wages, and at the same time the displaced workers could find other jobs and ultimately may not suffer any wage loss. This is possible because automation implies an increase in overall productivity and income.

[12] The two last panels in Table 9 report the results when rents are distributed according to the income distribution but only to skilled workers (college complete) or alternatively to non-routine workers.

of automation on inequality could be very sizeable, especially without some mechanism that allows distributing the proceeds of the technological advances to all the population.

5. Concluding remarks

According to our preferred estimates, the ongoing process of automation is not likely to make a very large dent on the rate of employment in Latin America. Instead, it is more likely for the expected technological changes to significantly affect the *structure* of employment. Unskilled and especially semi-skilled workers are likely to bear a disproportionate share of the adjustment costs, since the automatability of their occupations is higher compared to skilled workers. Therefore, automation will probably be a more serious threat for income equality than for overall employment.

The results entail a general policy implication. In the short and medium term, dislocation can be severe for certain types of work, and inequality may rise. This likely outcome will call for policies to smooth the adjustments caused by shifts in demand against low and medium paid jobs, especially for those groups of workers who could be most affected (the less educated and the youngsters). In the transition period, policies will be needed to facilitate labor market flexibility and mobility, introduce and strengthen safety nets and social protection, and improve education and training.

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Table 1: Proportion of jobs with high risk of automation, by occupation
Alternatives 1 and 2

Occupation	ISCO	High risk of automation A1	High risk of automation A2
Chief Executives, Senior Officials and Legislators	11	0.4%	8.8%
Production and Specialized Services Managers	13	0.6%	10.4%
Hospitality, Retail and Other Services Managers	14	3.5%	14.8%
Science and Engineering Professionals	21	0.5%	11.1%
Health Professionals	22	0.4%	3.6%
Teaching Professionals	23	0.2%	7.1%
Business and Administration Professionals	24	0.9%	33.6%
Information and Communications Technology Professionals	25	0.3%	11.8%
Legal, Social and Cultural Professionals	26	0.5%	16.8%
Science and Engineering Associate Professionals	31	3.3%	49.0%
Health Associate Professionals	32	4.3%	37.0%
Business and Administration Associate Professionals	33	4.9%	52.7%
Legal, Social, Cultural and Related Associate Professionals	34	1.3%	37.1%
Information and Communications Technicians	35	2.0%	55.2%
General and Keyboard Clerks	41	12.0%	94.0%
Customer Services Clerks	42	22.2%	71.6%
Numerical and Material Recording Clerks	43	13.0%	93.5%
Other Clerical Support Workers	44	11.6%	83.5%
Personal Services Workers	51	19.1%	48.2%
Sales Workers	52	32.4%	78.5%
Personal Care Workers	53	5.9%	42.3%
Protective Services Workers	54	7.7%	40.3%
Market-oriented Skilled Agricultural Workers	61	8.3%	71.0%
Market-oriented Skilled Forestry, Fishery and Hunting Workers	62	8.3%	74.0%
Building and Related Trades Workers (excluding Electricians)	71	12.2%	70.0%
Metal, Machinery and Related Trades Workers	72	15.2%	72.9%
Handicraft and Printing Workers	73	13.0%	61.6%
Electrical and Electronic Trades Workers	74	10.0%	54.9%
Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers	75	18.5%	71.3%
Stationary Plant and Machine Operators	81	27.7%	84.4%
Drivers and Mobile Plant Operators	83	31.1%	64.2%
Cleaners and Helpers	91	20.8%	63.5%
Agricultural, Forestry and Fishery Labourers	92	8.3%	88.0%
Labourers in Mining, Construction, Manufacturing and Transport	93	34.4%	70.9%
Food Preparation Assistants	94	34.6%	86.0%
Street and Related Sales and Services Workers	95	29.9%	94.0%
Refuse Workers and Other Elementary Workers	96	33.6%	77.9%

Table 2: National household surveys used in the analysis

country	survey	acronym	Years
Argentina	Encuesta Permanente de Hogares	EPH	2016-2018
Brazil	Pesquisa Nacional por Amostra de Domicilios	PNAD	2017-2019
Chile	Encuesta de Caracterización Socioeconómica Nacional	CASEN	2017
Colombia	Gran Encuesta Integrada de Hogares	GEIH	2016-2018
Mexico	Encuesta Nacional de Ingresos y Gastos de los Hogares	ENIGH	2016 & 2018
Peru	Encuesta Nacional de Hogares	ENAHO	2016-2018

Table 3: Harmonization of occupation codes

Country	Occupational classification	ISCO-08 harmonization process
ARG	Clasificador Nacional de Ocupaciones	Official crosswalk provided by INDEC
BRA	Classificação de Ocupações para Pesquisas Domiciliares	Own ad-hoc crosswalk
CHL	International Standard Classification of Occupations	Own ad-hoc crosswalk based on ILO official crosswalk
COL	Clasifiación Nacional de Ocupaciones	Own ad-hoc crosswalk based on DANE crosswalk and individual's educational
MEX	Sistema Nacional de Clasificación de Ocupaciones	Own ad-hoc crosswalk
PER	Código de Ocupaciones	Own ad-hoc crosswalk based on INEI crosswalk

Source: own elaboration.

Table 4: Proportion of jobs with high risk of automation, by country

Alternatives 1 and 2

	A1	A2
Argentina	16.3%	59.9%
Brazil	16.3%	59.7%
Chile	15.4%	57.0%
Colombia	17.0%	63.5%
Mexico	18.4%	64.2%
Peru	16.8%	67.6%
Latin America	16.7%	62.0%

Source: own calculations based on microdata from national household surveys.

Table 5: Proportion of jobs with high risk of automation, by region
Alternatives 1 and 2

		High risk of automation	
Country	Region	A1	A2
Argentina	Gran Buenos Aires	0.162	0.597
Argentina	Pampeana	0.163	0.601
Argentina	Cuyo	0.167	0.605
Argentina	Noroeste Argentino	0.167	0.602
Argentina	Patagonia	0.148	0.605
Argentina	Noreste Argentino	0.161	0.609
Brazil	Norte	0.159	0.631
Brazil	Nordeste	0.169	0.633
Brazil	Sudeste	0.157	0.594
Brazil	Sur	0.152	0.606
Brazil	Centro-Oeste	0.161	0.605
Chile	Tarapacá	0.167	0.562
Chile	Antofagasta	0.158	0.560
Chile	Atacama	0.164	0.591
Chile	Coquimbo	0.168	0.624
Chile	Valparaíso	0.152	0.578
Chile	Libertador Gral. B. O'Higgins	0.152	0.645
Chile	Maule	0.148	0.638
Chile	BioBío	0.163	0.594
Chile	Araucanía	0.145	0.587
Chile	Los Lagos	0.149	0.595
Chile	Aysén del Gral. Carlos Ibáñez	0.139	0.545
Chile	Magallanes y de la Antártica	0.138	0.533
Chile	Región Metropolitana de Santiago	0.145	0.533
Chile	Los Ríos	0.148	0.576
Chile	Arica y Parinacota	0.147	0.564
Chile	Ñuble	0.148	0.641
Colombia	Atlántica	0.183	0.615
Colombia	Oriental	0.172	0.622
Colombia	Central	0.174	0.623
Colombia	Pacífica	0.175	0.614
Colombia	Santa Fe de Bogotá	0.168	0.580
Mexico	Noroeste	0.179	0.641
Mexico	Norte	0.184	0.660
Mexico	Noreste	0.188	0.650
Mexico	Centro-Occidente	0.187	0.660
Mexico	Centro-Este	0.193	0.650
Mexico	Sur	0.163	0.684
Mexico	Oriente	0.175	0.667
Mexico	Peninsula de Yucatan	0.177	0.641
Peru	Costa Urbana	0.188	0.648
Peru	Sierra Urbana	0.173	0.630
Peru	Selva Urbana	0.180	0.651
Peru	Costa Rural	0.137	0.754
Peru	Sierra Rural	0.117	0.767
Peru	Selva Rural	0.114	0.768
Peru	Lima Metropolitana	0.179	0.612

Source: own calculations based on microdata from national household surveys.

Table 6: Proportion of jobs with high risk of automation, by sector

	High risk of automation	
Occupation	A1	A2
Agriculture & forestry	9.5%	77.0%
Fishing	10.8%	73.8%
Mining & quarrying	19.2%	61.4%
Manufacturing	18.8%	67.6%
Utilities	14.8%	60.3%
Construction	17.5%	65.9%
Commerce	25.6%	73.0%
Restaurants & hotels	21.3%	61.1%
Transportation & communications	25.0%	63.0%
Finance	11.1%	58.9%
Business services	11.0%	50.2%
Public administration	10.4%	52.6%
Teaching	4.4%	23.2%
Haealth & social services	7.1%	36.2%
Other services	15.5%	52.0%
Domestic servants	18.9%	61.2%
Extra-territorial organizations	6.9%	44.8%
Total	16.7%	62.0%

Source: own calculations based on microdata from national household surveys.

Table 7: Proportion of jobs with high risk of automation, by gender

	High risk of automation	
	A1	A2
Females	16.5%	60.2%
Males	16.8%	63.3%
Total	16.7%	62.0%

Source: own calculations based on microdata from national household surveys.

Table 8: Gini coefficient of labor income
Alternative impact of automation on labor incomes of affected workers

Beta	ARG	BRA	CHL	COL	MEX	PER	Average
1	40.6	50.3	46.4	47.9	49.9	47.0	47.0
0.75	41.4	51.3	47.4	48.8	50.7	47.7	47.9
0.5	43.1	53.0	49.2	50.5	52.4	49.2	49.6
0.25	46.0	55.5	51.8	53.3	55.2	52.0	52.3
0	50.2	59.2	55.3	57.4	59.7	56.6	56.4

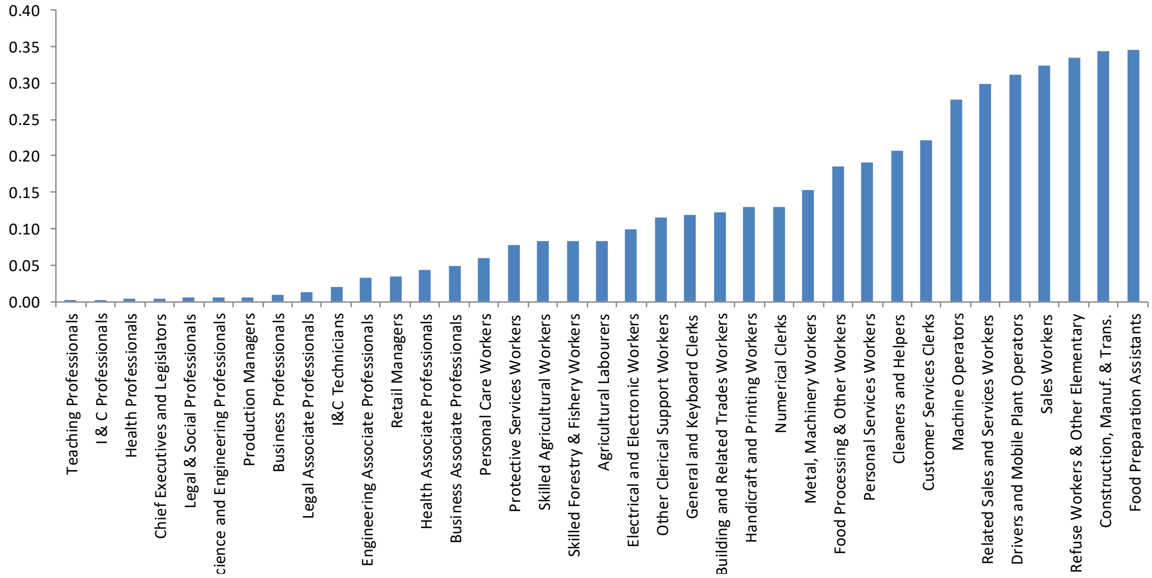
Source: own calculations based on microdata from national household surveys.

Table 9: Gini coefficient of household per capita income
Alternative impact of automation

		Beta				
		1	0.75	0.5	0.25	0
Mean original Gini	45.6					
Top percentile - 100%		52.1	53.3	55.6	60.3	74.8
Top percentile - 50%		49.0	49.7	51.2	54.9	69.4
Capital income - 100%		53.6	55.3	58.0	63.4	77.5
Capital income - 50%		49.7	50.7	52.5	56.7	71.5
Income - 100%		46.9	47.1	47.6	49.7	63.0
Income - 50%		46.3	46.3	46.8	48.8	62.2
Income (skilled workers) - 100%		52.3	53.5	55.6	59.7	73.3
Income (skilled workers) - 50%		49.2	49.9	51.3	54.6	68.7
Income (non-routine workers) - 100%		48.9	49.3	50.0	52.0	64.6
Income (non-routine workers) - 50%		47.6	47.8	48.4	50.6	63.6

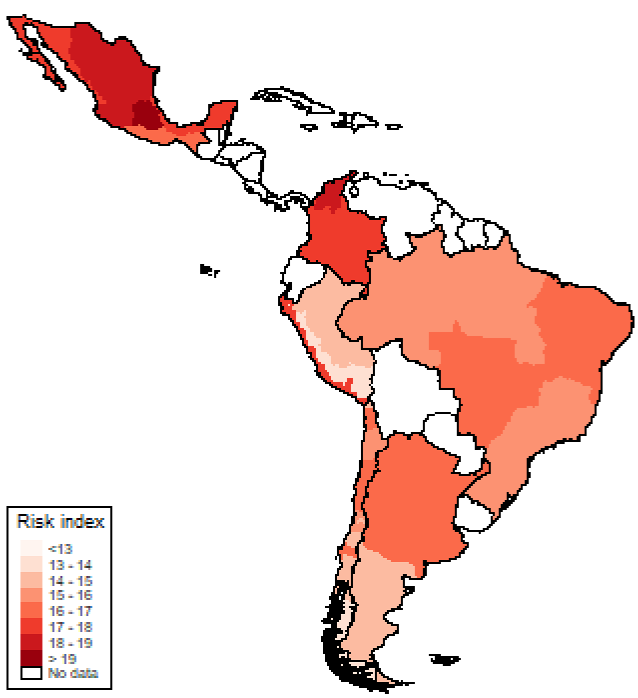
Source: own calculations based on microdata from national household surveys.

Figure 1: Proportion of jobs with high risk of automation, by occupation



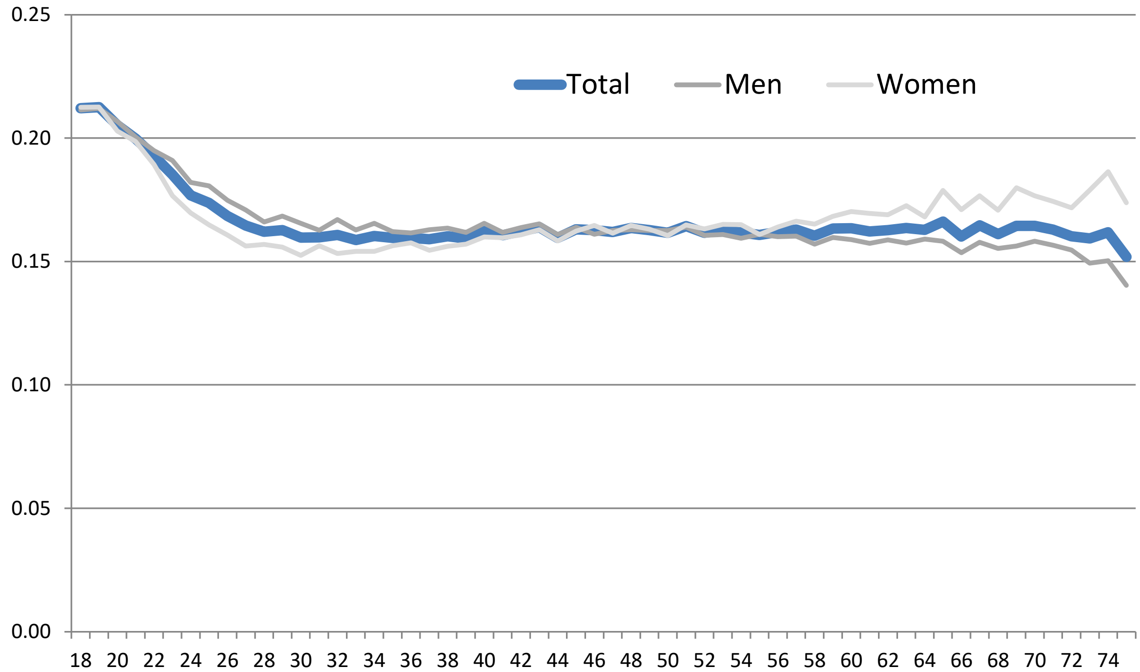
Source: own calculations based on methodological alternative 1. See text for details.

Figure 2: The risk of automation by region



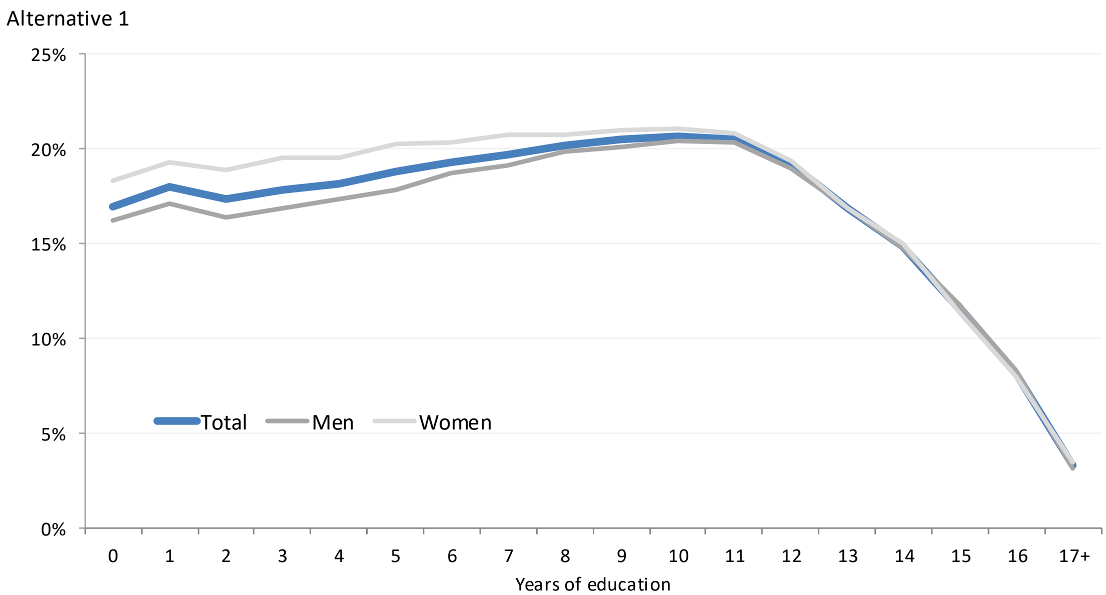
Source: own calculations based on microdata from national household surveys.

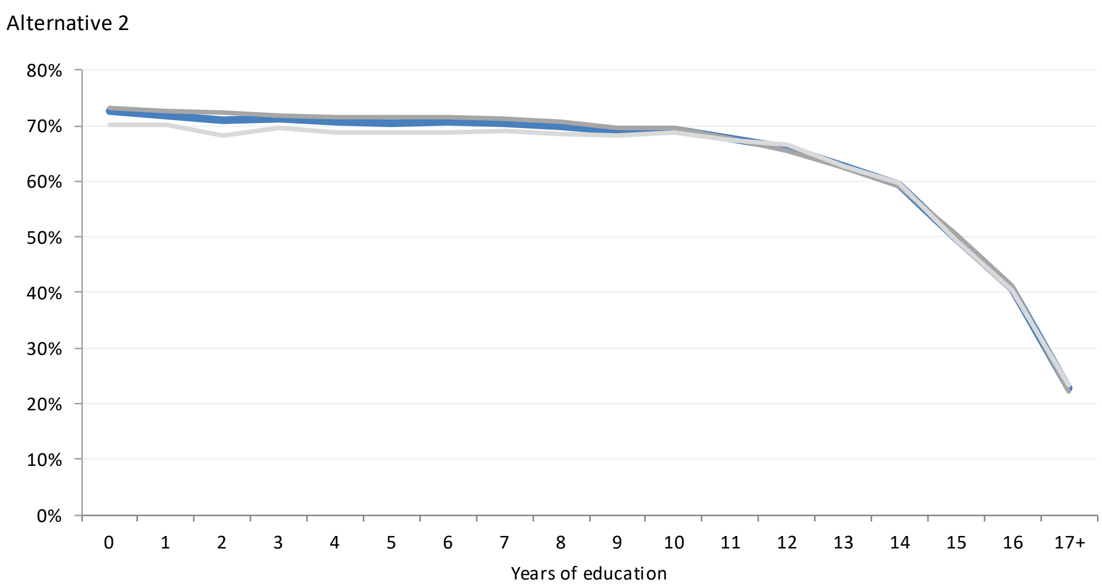
Figure 3: Proportion of jobs with high risk of automation, by gender and age
Alternative 1



Source: own calculations based on microdata from national household surveys.

Figure 4: Proportion of jobs with high risk of automation, by years of education.

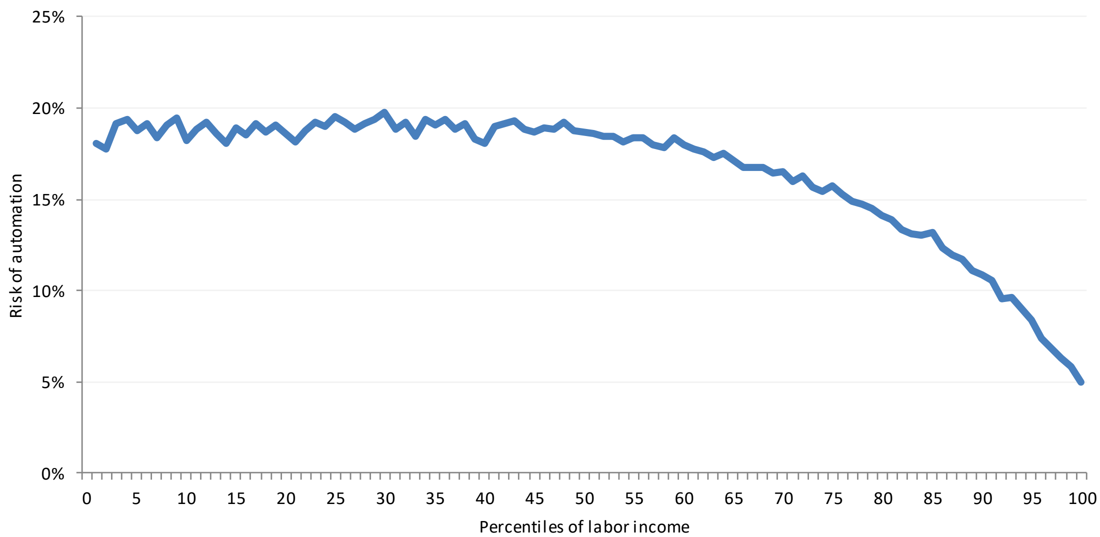




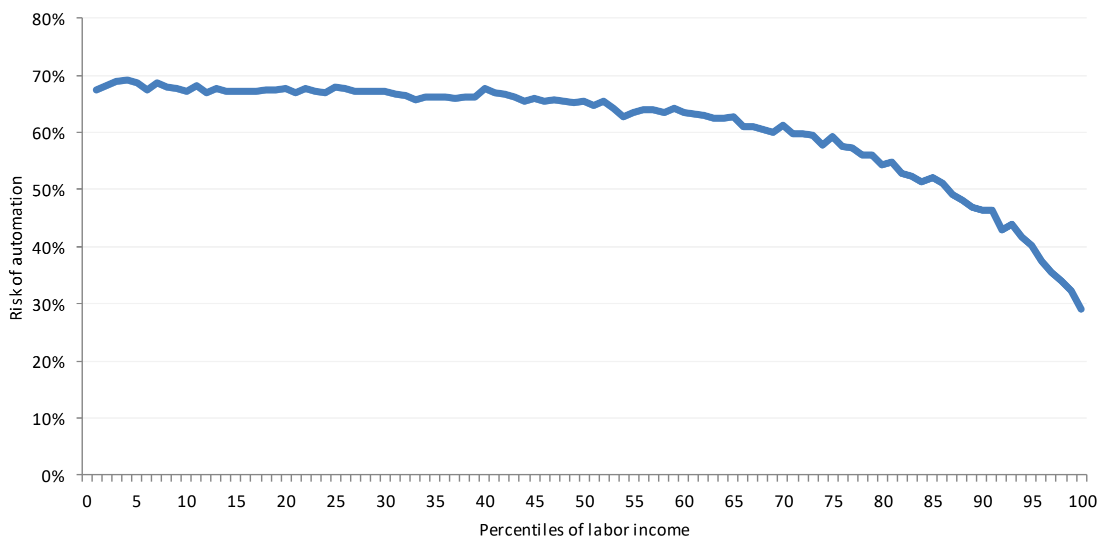
Source: own calculations based on microdata from national household surveys.

Figure 5: Proportion of jobs with high risk of automation, by earnings percentiles

Alterative 1



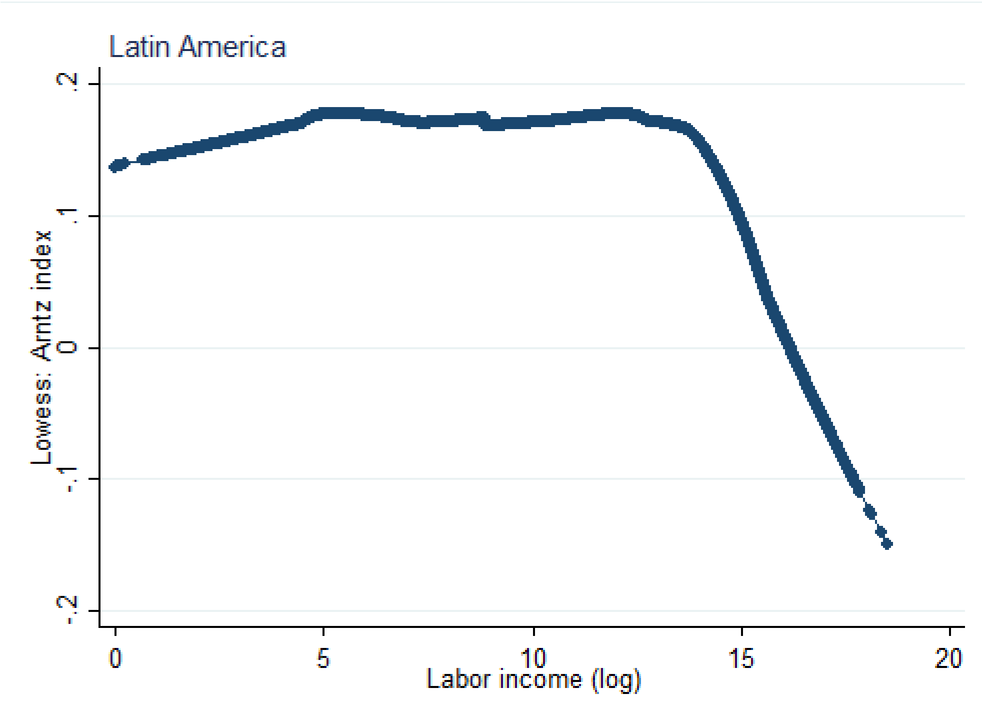
Alterative 2



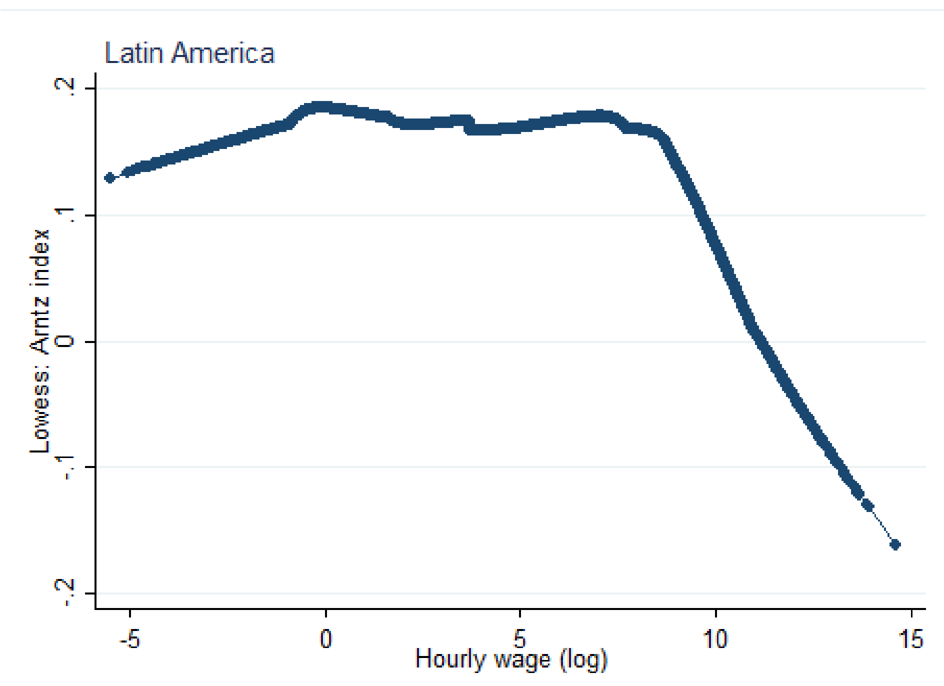
Source: own calculations based on microdata from national household surveys.

Figure 6: Proportion of jobs with high risk of automation, by earnings and wages. Non-parametric estimation (lowess regressions)

Monthly labor income

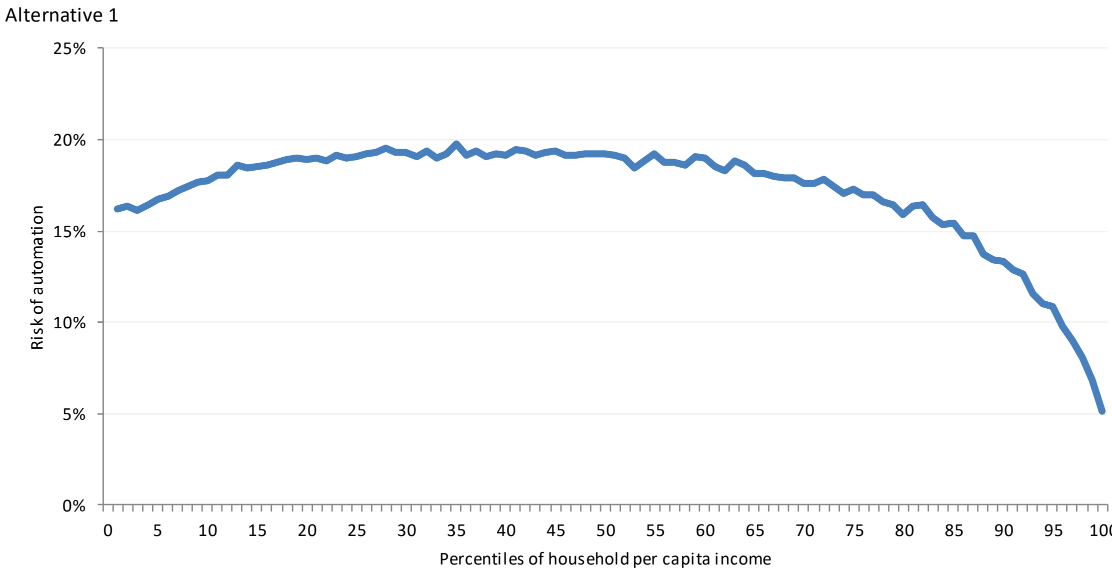


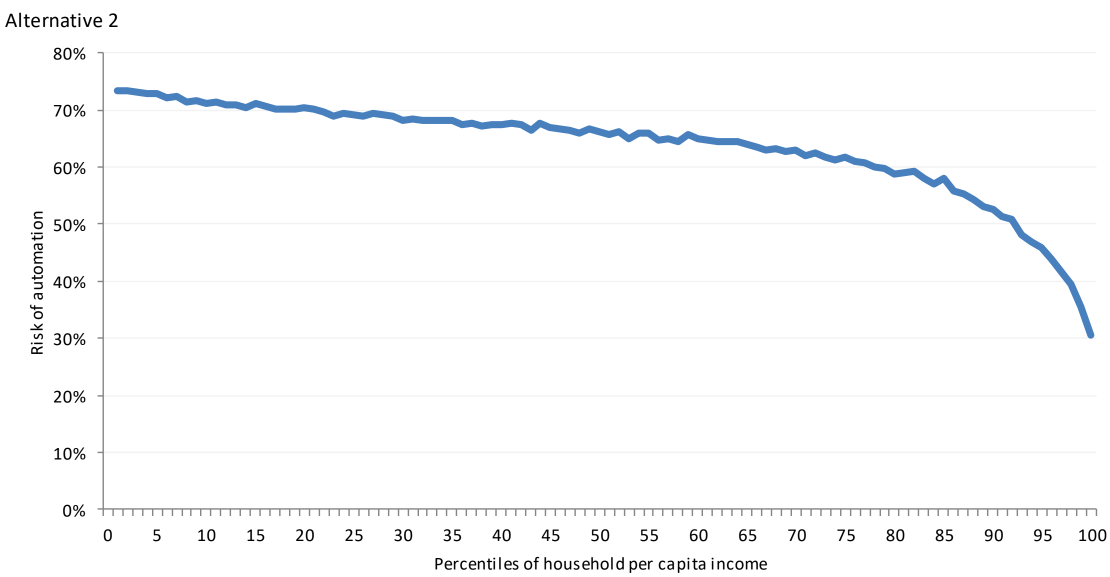
Hourly wages



Source: own calculations based on microdata from national household surveys.

Figure 7: Proportion of jobs with high risk of automation, by household per capita income percentiles





Source: own calculations based on microdata from national household surveys.