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Abstract[1]

This paper studies the effects of automation of production on labor market outcomes, and whether there is an effect of automation on functional and personal inequality in Latin America. The paper combines several data sources and empirical strategies in order to approach the issues from different perspectives and to cover different dimensions of labor markets. The main issues that we focus on are: i) the hypothesis that industries with a higher share of workers performing routine tasks are more likely to be affected by automation, using indexes of task routinization by occupation; and ii) the effects of automation on industry and local labor share, employment, wages, personal inequality and poverty. We focus on seven Latin American countries: Argentina, Brazil, Chile, Colombia, Ecuador, Mexico and Peru, during the period 1992–2015.

Keywords: automation, labor share, labor markets, functional inequality, personal inequality, Latin America

JEL codes: J21, J24, O33

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1 Introduction

In the last two decades there has been a sharp increase in the use of robots and digital technology all over the world. Concerns about machines replacing workers are not new and date back to the Industrial Revolution, but more recent computer-based technologies are different in that they offer the possibility of completely automating some tasks.[2] This paper aims to study the effects of automation of production on labor market outcomes, and to establish whether there is an effect of automation on functional and personal inequality in Latin America.

The early literature on skilled-biased technological change dates back to the seminal work of Katz and Murphy (1992), Bound and Johnson (1992) and Card and Lemieux (2001). This literature assumes that technology is complementary with skilled labor, therefore positively affecting the relative demand and wage of skilled workers. 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, Levy and Murnane (2003) and Acemoglu and Autor (2011). The task approach argues that the complementarity with or substitutability between technology and labor does not occur at the worker skill level but rather depending on how susceptible different tasks are to automation.[3] Occupations that involve creative thinking, problem-solving, interpersonal skills, and those that are not repetitive, are not susceptible to being codified by a computer and are less prone to automation, whereas tasks that are repetitive and routinary may be more susceptible to being carried out by technology instead of workers.

The major concern is that new technologies may displace a significant share of workers from the labor market. At the same time, as firms become more productive due to cost-

[2]Examples include robotization of automobile and electronic industries, e-commerce platforms, and online check-in for airlines.

[3]Unlike the early literature, they conclude that tasks performed by workers in the middle of the skill distribution are more likely to be substitutable by machines, thus leading to the polarization hypothesis (Autor et al., 2003; Spitz-Oener, 2006; Goos and Manning, 2007; Goos et al., 2014 and Michaels et al., 2014; Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014).

saving technology and hire workers who are complementary with technology, wages may go up for employed workers. The main focus of our analysis are changes in the labor share, employment, and wages that are due to technology adoption. We also study changes in the distribution of income and poverty. We seek to answer these questions empirically for a set of seven Latin American countries: Argentina, Brazil, Chile, Colombia, Ecuador, Mexico and Peru. We use household survey data and industrial data for the years 1992 to 2015.

Our empirical strategy is based on the combination of two ideas. First, we follow the task-based approach and define a routine task content (RTC) index at the industry level and at the district level. The RTC index is a number between zero and one that quantifies how susceptible workers in an industry and district are to automation based on occupational structure and the tasks they perform. Second, we exploit the acceleration of adoption of automation technology across time, proxied by the stock of industrial robots. We use the exposure to automation across occupations and across time to construct a difference-in-differences estimator of the causal relation between adoption of automation technology and labor market outcomes.

At the industry level we study the labor share (wage bill participation in output), average industry wage, average industry employment, and share of industry in total employment. We construct an RTC index at the industry level from the tasks reported in the Survey for Adult Skills of the PIAAC program at the OECD, which includes information about tasks in Latin American countries. At the local level we compute the employment rate, average wage, inequality, and poverty rate for each district in each country. We compute occupation level indexes from the PIAAC surveys, and then construct district-level indexes as a weighted average of the occupation level indexes. The industry and district RTC indexes capture the percentage of people in the industry or district who perform routine tasks.

We take into consideration that, while technology adoption is a process that has been under way for decades, more recent automation technology is unique in its amenability to codification and therefore in its potential impact on labor markets. Workers who perform routine tasks become more vulnerable as digital technology and robotics become available, cost-effective and widespread. In our sample period 1992–2015, there is a sharp acceleration in the adoption of robots around 2005. We split the sample in three time periods: 1992–1998, 1999–2004, 2005–2015, and compute two separate difference-in-differences estimators, one for the first two time periods, and the other for the last two time periods. In this manner, we test the idea that the link between routinization and labor market outcomes is shaped by automation as a particular form of technological progress.

We find that, after the acceleration of technology adoption that occurs mid-sample, employment decreases more rapidly in industries with a high RTC index, supporting the idea that machines replace workers that perform repetitive tasks. The labor share, however, remains unchanged on average, as wages of workers who remain employed weakly go up. Findings at the local labor market level are consistent with the industry-level results. Unemployment increases in districts with a high RTC index. At the same time, due to increases in productivity and changes in composition of the labor force, the average wage increases and the informality rate decreases. This points towards unequal distribution of the gains from automation technology. Some workers are displaced by technology, while workers who remain employed enjoy better working conditions. We further find that unemployment increases more rapidly among unskilled workers, while poverty and inequality increase as well.

Our paper most closely relates to Autor, Levy and Murnane (2003) and Autor, Katz and Kearney (2006, 2008). There is also a large set of papers that study the impact of technology on jobs directly, without relying on the task-based hypothesis. Autor and Dorn (2013) study the impact of computerization on the demand for low-skilled labor, Michaels et al. (2014) study whether ICT has contributed to the rise in polarization, and Akerman et al. (2015) study skill complementarity of broadband internet in Norway. A regional study led by the World Bank looks at several case studies of digital technology adoption in Latin America (see Dutz et al., 2018, for a survey). Regarding robotization, Graetz and Michaels (2018) find that industrial robots increase labor productivity and value added in 17 developed countries.

Acemoglu and Restrepo (2018) find that robots reduce employment in US labor markets, and Autor and Salomons (2018) find that there are spillovers across industries that increase aggregate demand. As a general rule, most studies refer to the US and European labor markets, whereas the evidence for Latin America is much scanter. In addition to Dutz et al. (2018), a few papers have studied the labor market polarization hypothesis in developing countries (Messina and Silva, 2017; Maloney and Molina, 2018; and Das and Hilgenstock, 2018).

The paper is organized as follows. In the next section we describe the data. In the following two sections we describe the empirical approach used in the industry-level and district-level regressions. Section 5 concludes.

2 Data

The paper is data-intensive. The outcomes that we study are based on the combination of two main different types of data: industry-level data on employment and production, and household-level data on labor market outcomes at the individual level.

Table 1 shows a brief overview of the outcome data. Industry-level data come from UNIDO. From the UNIDO data we are able to compute labor shares and share of industry in total employment at the 2-digit industry level.

At the individual level, we put together more than 100 household surveys from Argentina, Brazil, Chile, Colombia, Ecuador, Mexico and Peru, from 1992 to 2015. The household surveys come from SEDLAC and include information on wages, worker characteristics such as age and education, industry affiliation and occupation that we standardize across countries.[4] We use these data to study local labor markets. We construct measures of the employment rate, average wage, inequality and poverty at the district level.

There are data gaps for some countries. UNIDO data are not available for Argentina for

[4] The SEDLAC database is a joint project between CEDLAS-UNLP and The World Bank. See http://www.cedlas.econo.unlp.edu.ar/wp/en/estadisticas/sedlac/.

Table 1: Summary of Data Sources

	Industrial statistics (UNIDO)		Household surveys (SEDLAC)	
	Total obs.	Years	Total obs.	Years
	(1)	(2)	(3)	(4)
Argentina	200	10	3483294	24
Brazil	472	24	7709716	21
Chile	301	20	2227951	11
Colombia	459	24	7178032	13
Ecuador	470	24	1091602	13
Mexico	292	15	941101	13
Peru	418	24	1488704	19
All countries	2612	141	24120400	101

Notes: Years 1992-2015. Data from UNIDO are at the 2-digit level of the ISIC Revision 3 classification. Data from household surveys are at the individual-level. Columns (1) and (3) show the total number of observations for each country. Columns (2) and (4) show the total number of years of data for each country.

the time period 2005–2015, and SEDLAC data are not available for Colombia and Ecuador for most years before 2005. Overall, we have information on more than 24,000,000 surveyed individuals (column 3) and more than 2,600 country–industry pairs (column 1). More details about the two data sources are given in Appendix A.

Tables 2 and 3 present descriptive statistics. Table 2 shows the average share of labor in each country during the period 1992–2015. The labor share is defined as the participation of the wage bill in total value of production. It ranges from 0.15 in Ecuador to 0.35 in Argentina (column 1). Columns 1 and 2 report the shares in two time periods, 1992–2004 and 2005–2015. The labor share has increased in Brazil, Ecuador and Mexico, and it has decreased in Chile, Colombia and Peru.[5] The largest change occurs in Colombia, with a decrease in the labor share of almost 6 percentage points (column 4). Other changes range from 0.2 to 2.1 percentage points. The average share across all countries, in both time periods, is 18 percent.

Table 3 presents descriptive statistics from household surveys. The average during 1992–

[5]UNIDO data are not available for Argentina for the time period 2005–2015.

Table 2: UNIDO industry data

	Labor share			
	All years (1)	1992–2004 (2)	2005–2015 (3)	Change (4)
Argentina	0.35	0.35	.	.
Brazil	0.23	0.22	0.24	0.020
Chile	0.21	0.22	0.20	-0.018
Colombia	0.13	0.15	0.10	-0.059
Ecuador	0.15	0.14	0.16	0.021
Mexico	0.16	0.15	0.16	0.009
Peru	0.20	0.20	0.20	-0.002
All countries	0.18	0.18	0.18	-0.005

Notes: Authors' calculations based on UNIDO data. The table shows the average labor share, defined as industry wage bill over industry value of output, for different time periods. The last line computes the average across all countries in the table except Argentina.

2015 of poverty rates, Gini coefficients, employment and labor income varies markedly across countries. The highest unemployment rates occur in Argentina, Colombia, Chile and Brazil. The highest poverty rates occur in Peru, Colombia, Ecuador and Mexico.

We match the outcome data with information on routinization and on technology adoption. Our baseline analysis involves relating labor market outcomes with the possibilities for automation involved in the tasks that workers perform. Tasks that involve routine repetitive actions are more prone to being performed by a machine, with the result that workers who perform these types of tasks are more vulnerable to automation. We use data from the Survey of Adult Skills from the Programme for the International Assessment of Adult Competencies (PIAAC), conducted by the OECD, to construct indexes of routinization task content (RTC).

The PIAAC survey is conducted in many countries. In Latin America there are PIAAC surveys for Chile, Ecuador, Mexico and Peru. The data for Chile were collected in the second round of PIAAC surveys, in 2014–2015, while the data for Ecuador, Mexico and Peru

Table 3: Descriptive Statistics from Household Surveys

	Poverty and inequality		Labor market		
	Poverty rate (1)	Gini coef. (2)	Employment rate (3)	Unemp. rate (4)	Labor income (5)
Argentina	20.7	0.48	63.3	11.0	799.1
Brazil	34.1	0.56	69.3	7.6	680.8
Chile	26.7	0.52	60.5	8.0	822.1
Colombia	41.9	0.54	67.4	11.1	630.8
Ecuador	37.3	0.50	69.8	5.3	597.0
Mexico	40.4	0.51	65.8	3.5	627.1
Peru	41.8	0.50	77.9	3.9	447.0
All countries	33.9	0.52	68.08	7.40	657.6

Notes: Authors' calculations from SEDLAC database. The table reports average statistics during 1992–2015. Poverty rate is the percentage of population with income below the official poverty line. Labor market statistics restricted to adults aged 18–65. Employment is the share of adults employed. Unemployment is the share of adults in the labor force who have been actively looking for a job in the last month. Labor income is the monthly value expressed in constant USD PPP 2011.

was collected in the third round of surveys, in 2017.[6] Individuals answer detailed questions about education and training, about use of time, and about job-related activities. We focus on four specific job-related questions: Do you manage or supervise other people? Do you plan activities of other workers? Are you confronted with problems? Do you write articles or reports? The four questions reflect tasks that require creative thinking, flexibility, and problem-solving abilities that cannot be codified and replaced by technology. These tasks can be performed both in manual and cognitive occupations and, Importantly, they have high variability in responses across individuals. For each individual in the survey we define a flexibility index F_1. The index is a dummy variable that is equal to one when the individual replies that he performs at least one of the four tasks often or very often.

For robustness we define several additional flexibility indexes. Flexibility index F_2 is a

[6]The full list of countries is Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Ecuador, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Kazakhstan, Lithuania, Mexico, Netherlands, New Zealand, Norway, Peru, Poland, Republic of Korea, Russian Federation, Singapore, Slovakia, Slovenia, Spain, Sweden, Turkey, United Kingdom, and United States, for a total of 35 countries.

dummy variable that is equal to one when the individual replies positively to at least one of the four questions above, or to the following two additional questions: Do you calculate budgets or costs? Do you give presentations? Flexibility indexes F_3 and F_4 take values between 0 and 1 and capture the percentage of flexible tasks that the individual performs. For F_3 we consider the first four questions. The index can take values of 0, 1/4, 2/4, 3/4, 4/4 according to how many flexible tasks the individual performs. For F_4 we consider the longer list of six flexible tasks. The index can take values of 0, 1/6, 2/6, 3/6, 4/6, 5/6, 6/6 following the same logic. Flexibility index F_5 is constructed by performing MLE factor analysis to compute a linear combination of the six questions above into a single index. The index is normalized so that its mean is zero and its standard deviation is one. See Appendix A for more details on the construction of all indexes.

Table 4 shows descriptive statistics for the tasks and indexes. The first column shows the percentage of individuals, across all countries, that respond positively to performing flexible tasks: 12 percent for supervising, 28 percent for planning, 32 percent for solving problems, 31 percent for producing written output, 62 percent for giving presentations, and 37 percent for preparing budgets. The percentages across column 1 (all countries) and column 2 (Latin America) are very close, with the exception of preparing budgets, which occurs more often in Latin America. Across the four Latin American countries, more workers tend to perform flexible tasks in Chile and Mexico than in Ecuador and Peru. The flexibility indexes F_1 and F_2 represent the percentage of individuals that perform at least one flexible task (out of the first four tasks for F_1 and out of all the six tasks for F_2). The average across all countries are 59 and 81 percent. The indexes F_3 and F_4 represent the average percentage of flexible tasks performed. Across all countries the last two indexes are 26 and 34 percent, respectively Index F_5 is a linear combination of the six flexible tasks with weights obtained by performing factor analysis.[7]

For each individual in the PIAAC survey we also know their occupation according to the

[7]The mean of F_5 is not zero in Table 4 because it is computed using sampling weights.

ISCO 08 classification. We use this information to define a routinization task content index RTC_1 at the occupational level as the percentage of individuals in the occupation that do not perform any of the four activities above often. That is, for occupation i, the index is defined as

$$RTC_{1,i} = 1 - \frac{1}{n_i} \sum_h F_{1,h} \tag{1}$$

where h are individuals and n is the number of individuals in occupation i. Sampling weights are also considered in the computation of the index. The index captures the percentage of individuals within an occupation that mostly perform routine tasks. The higher the RTC of an occupation, the higher the possibilities of automation. We analogously define routine task content indexes RTC_2, RTC_3, RTC_4, RTC_5 by computing weighted averages of the individual level flexibility indexes F_2, F_3, F_4, F_5.[8] A similar approach is used by Autor, Levy, and Murnane (2003) and Autor, Katz, and Kearney (2006, 2008). We adapt these approaches to work with tasks data from the PIAAC survey, which allows us to work with information about tasks performed specifically by Latin American workers.

Individuals in the PIAAC survey also report their industry of employment according to the ISIC Revision 4 classification. We use this information to construct RTC indexes at the industry level. For industry j the index is

$$RTC_{1,j} = 1 - \frac{1}{m_j} \sum_h F_{1,h} \tag{2}$$

where m is the number of individuals in industry j. We proceed in an analogous manner to construct RTC_2, RTC_3, RTC_4, RTC_5 at the industry level.

Each Latin American PIAAC survey has between 2,000 and 4,000 observations on employed individuals (Table 4). Our empirical analysis involves workers in Argentina, Brazil, Chile, Colombia, Ecuador, Mexico and Peru. Four out of these seven countries have their own PIAAC survey, which we could in principle use separately. However, individuals are

[8]In the case of F_5 the index is defined as $RTC_{5,i} = (-1)\frac{1}{n_i}\sum_h F_{5,h}$.

Table 4: PIAAC surveys

	All Surveys (1)	Latin America (2)	Chile (3)	Ecuador (4)	Mexico (5)	Peru (6)
Supervising	0.12	0.11	0.14	0.09	0.12	0.08
Planning	0.28	0.25	0.31	0.28	0.25	0.20
Solving problems	0.32	0.31	0.39	0.25	0.32	0.24
Written output	0.31	0.30	0.35	0.30	0.31	0.22
Presentations	0.53	0.43	0.49	0.54	0.42	0.39
Budgets	0.37	0.50	0.45	0.51	0.51	0.51
F1	0.59	0.57	0.64	0.56	0.58	0.46
F2	0.79	0.80	0.83	0.81	0.80	0.77
F3	0.26	0.24	0.30	0.23	0.25	0.18
F4	0.32	0.32	0.35	0.33	0.32	0.27
F5	-0.004	-0.16	-0.01	-0.17	-0.16	-0.24
Observations	68959	11688	2539	2332	2949	3868

Notes: Table shows the percentage of individuals who respond "yes" to performing six flexible tasks often (Supervising, Planning, Solving problems, Producing written output, Giving presentations or sales pitches, Calculating budgets), the average of the four flexibility indexes across individuals (F_1, F_2, F_3, F_4, F_5), and the number of observations. Calculations are based on employed individuals who can be matched to an ISCO 08 occupation.

unevenly distributed across industries and occupations, which results in some industry-level and occupation-level RTC indexes being constructed with too few observations. To deal with this issue we pool together the four Latin American PIAAC surveys and construct the RTC indexes from the pooled surveys from all countries. This procedure relies on the assumption that the composition of tasks within industries and within occupations is the same across countries. We test this assumption empirically by comparing indexes for occupations and industries that have a sufficiently large number of observations for each country. We construct indexes computed from the pool of the four Latin American countries, and for each of the four Latin American countries taken separately. Table A1 of Appendix A shows that the correlation is indeed very high, always above 80 percent for occupations and above 75 percent for industries, and in several cases above 90 percent. We thus proceed with the RTC indexes computed from all surveys and include all industries and occupations in the analysis.[9]

Indexes constructed from the PIAAC surveys reflect tasks reported by Latin American workers. Since they are computed at the industry level directly from the pooled PIAAC surveys, they do not vary across countries. For reasons of completeness, we construct an additional index using the occupation index of Autor and Dorn (2013), which is based on the U.S. Dictionary of Occupational Titles (DOT) from 1977. We average the occupation level index using occupation shares in total industry employment to construct industry level indexes. Because it is not computed directly from industry information, this index does vary across countries together with the different occupation weights. We refer to this index as RTC_6.

Additional information about the indexes is reported in Appendix A. Tables A2 and A3 show the RTC indexes across industries and across occupations. The least flexible industries are Textiles, Leather, Apparel, Wood, and some Mineral products. The most flexible industries are Coke and petroleum, Computers and electronics, and Chemicals. At the occupation level, flexibility is highly correlated with skills (Table A3).[10] Figure A1 shows that there is high correlation between RTC_1 and the alternative definitions of the RTC indexes (RTC_2 to RTC_6) at both the industry level and the occupation level.

3 Labor Share at the Industry Level and the Task Content of Jobs

In this section we study the impact of automation on the labor share. It is based on data from UNIDO. Across industries, workers perform different types of tasks, some of them more

[9]Table 4 shows that the propensity to perform flexible tasks differs across countries. This is consistent with tasks being similar across countries *within occupations and industries*, and may represent differences across countries in the composition of industries and occupations in total employment.

[10]The occupation-level indexes are constructed with a higher number of observations than the industry-level indexes. This is because we build the RTC industry level indexes to match the UNIDO data, which only include information on manufacturing. Surveyed individuals who work in services are used to build the occupation-level indexes but not the industry-level indexes.

susceptible to being replaced by technology than others. Non-routine tasks that involve creative thinking and problem-solving are difficult to automatize, whereas routine tasks that are repetitive and may be codifiable are more prone to being performed by machines. Routine tasks may be manual, in which case they may be carried out by production machinery such as robots, or cognitive, and may be carried out with digital technology. To test the impact of automation on the labor share we use the industry-level routine task content (RTC) index defined in equation (2). The industry RTC index captures how many workers perform routine tasks in each industry.

In our baseline specification, we split the data into three time periods: $t_0 = 1992 - 1998$, $t_1 = 1999 - 2004$, and $t_2 = 2005 - 2015$ and compute the average variables of interest for each time period, so that for each industry–country we have three time-varying observations. We run the following set of regressions

$$\Delta y_{jt1} = \gamma_1 + \alpha_1 RTC_j + x'_{jt0}\delta_1 + \Delta\epsilon_{jt1} \quad (3)$$

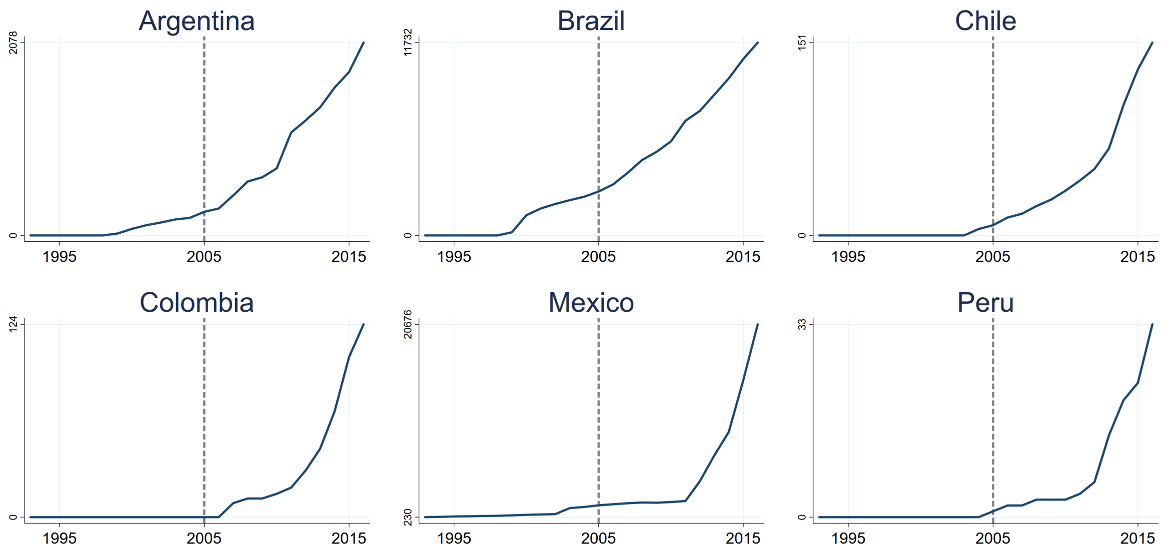
$$\Delta y_{jt2} = \gamma_2 + \alpha_2 RTC_j + x'_{jt0}\delta_2 + \Delta\epsilon_{jt2} \quad (4)$$

where Δy is the change in outcome variables at the industry level, x_0 are initial characteristics that capture differential trends across industries and countries, and ϵ is a random error term. In the first regression, the changes Δ are computed for the time periods t_1 and t_0, whereas in the second regression, the changes Δ are computed for the time periods t_2 and t_1. The outcome variables are industry employment, average industry wage, the labor share in the industry, industry share in total employment and industry output.

The choice of time periods is based on Figure 1, which shows the adoption of robots in six of the countries in our analysis.[11] We take the adoption of robots as an approximation of adoption of automation technology. Trends are not identical across countries, but as a general rule there is a marked acceleration in the adoption of robots in 2005. We therefore

[11] The data on robots, which come from the International Federation of Robotics, do not include information for Ecuador.

Figure 1: Trends in Adoption of Automation Technology



Notes: total number of robots. Source: International Federation of Robotics (IFR).

take 2005 as the initial year of period t_2. Regression equation (4) represents a difference-in-differences estimator, where we compare a *pre* automation technology period (1999–2004) and a *post* automation technology period (2005–2015). Exposure to automation varies across industries according to their routine task content RTC. The coefficient of interest is α_2, which captures the effect of automation on the outcome variables.

Regression equation (3) compares two sample periods that are *pre* automation technology (1992–1998, and 1999-2004). This regression is similar in spirit to a falsification experiment. Technology adoption is a continuous process that has been underway for decades. However, more recently and fairly abruptly, it has taken the form of automation technology, with the unique characteristic that tasks can be codified and thus put workers who perform routine tasks at risk. The objective of regression (3) is to test whether the link between routinization (as measured by the RTC index) and labor market outcomes has indeed been affected by the break in trend in automation technology that occurs around 2005, rather than having followed a continuous and monotonous evolution process. A break in trend in the link between rutinization and labor market outcomes is reflected in differences in coefficients α_1 and α_2.

In regressions (3) and (4) the main regressor is RTC, which is in principle not a firm decision variable but rather an objective description of the tasks involved in a job. The index is, however, based on task composition across industries, which is an endogeneous choice. To minimize endogeneity concerns, we work with an RTC index that is fixed over time, and we argue that its level does not correlate with the change in random shocks $\Delta\epsilon$. We also build the index RTC using data from several countries, as described in the data section, so that the task content of occupations does not correlate with specific country-level shocks. In the case of RTC_6, the index based on the occupation index of Autor and Dorn (2013), we use weights from the initial year of data to compute the industry average. The regression in differences controls for country-industry fixed effects.

In Table 5 we show results for industry employment, average industry wage and the share of labor in industry value of production. It is informative to look at the three variables together because the evolution of the share of labor is determined by both employment and wages. Odd columns (1, 3, 5) correspond to changes in outcome between t_1 and t_0 (regression equation 3), whereas even columns (2, 4, 6) correspond to changes between t_2 and t_1 (regression equation 4). The different horizontal panels correspond to the different definitions of the RTC index. As expected, different results emerge for the two time periods.

Changes between t_2 and t_1, our diff-in-diff strategy, show that differences in exposure to routinization across industries are associated with a decrease in employment (column 2). Taking the first definition of the index, RTC_1, a 10 percent difference in routinization across industries is associated with a relative decrease in employment of 7 percent in the second time period. Decreases of 9.2, 9.7, 10.2, 3.9 and 5.6 percent are estimated for the other definitions of the routinization index.[12] All these estimates are statistically significant except for the RTC_6 index based on Autor and Dorn (2013), which is nonetheless similar to the other indexes in magnitude of the point estimate. In contrast, the impacts on the RTC index on changes between t_1 and t_0 are not statistically significant, with the majority of the point

[12] These results are not effects on the *level* of employment, but rather relative differences across districts with different routinization indexes.

Table 5: Industry-Level Regressions

	Log employment		Log wage		Labor share	
	Δ_1	Δ_2	Δ_1	Δ_2	Δ_1	Δ_2
	(1)	(2)	(3)	(4)	(5)	(6)
RTC1						
	0.24	-0.70	-0.39	0.18	-0.15	0.03
	(0.30)	(0.24***)	(0.21*)	(0.20)	(0.05***)	(0.05)
RTC2						
	-0.15	-0.92	-0.31	0.22	-0.10	0.05
	(0.47)	(0.38**)	(0.33)	(0.31)	(0.07)	(0.07)
RTC3						
	0.36	-0.97	-0.47	0.43	-0.17	0.04
	(0.42)	(0.30***)	(0.31)	(0.30)	(0.07**)	(0.05)
RTC4						
	0.11	-1.22	-0.48	0.52	-0.15	0.05
	(0.55)	(0.38***)	(0.42)	(0.41)	(0.09*)	(0.07)
RTC5						
	-0.03	-0.39	-0.11	0.08	-0.04	0.02
	(0.13)	(0.09***)	(0.10)	(0.13)	(0.02*)	(0.02)
RTC6						
	2.20	-0.56	-1.56	1.15	-0.61	0.21
	(0.70***)	(0.64)	(0.67**)	(0.47**)	(0.26**)	(0.18)
Obs.	118	102	118	102	118	102

Notes: Dependent variables are: columns (1) and (2) industry log employment, columns (3) and (4) industry log average wage, columns (5) and (6) industry share of labor. Table shows coefficients α_1 and α_2 from regression equations (3) and (4). Columns (1), (3), (5) refer to changes in outcome defined as $t_1 - t_0$. Columns (2), (4), (6) refer to changes in outcome defined as $t_2 - t_1$. Regressions control for initial labor share, initial log value added per worker, and change in log value added per worker. Results are robust to different combinations of the control variables. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

estimates being positive, suggesting that the negative association between routinization and employment indeed occurs due to automation and is not a result of a continuous process of technology adoption spanning decades.

The effects on wages are not precisely estimated. Estimates in column 4 are positive but only significant for RTC_6. The reduction in employment and the (non-significant) increase in wages work in opposite direction, resulting on net effects on the labor share that are not significant, with point estimates close to zero. Changes between t_1 and t_0 show a decrease in the labor share between t_0 and t_1.

To further explore the time-varying effects of routinization on labor market outcomes we adopt the following regression specification

$$\widetilde{\Delta} y_{jt} \;=\; \gamma_3 + \alpha_3 RTC_j + \alpha_4 RTC_j \times Tech_{ct} + x'_{jt0}\delta_3 + \widetilde{\Delta}\epsilon_{jt}. \tag{5}$$

The regression equation is similar to the linear specification in (3) and (4) but differs in that we work with annual data instead of computing averages across three time periods, and in that we parameterize technology adoption. The variable $\widetilde{\Delta} y_t$ denote changes in y computed between t and t_0, the initial year of data, as in Autor, Katz and Kearney (2008). The variable $Tech$ represents the degree of automation technology adoption in country c at time t. We approximate the variable $Tech$ with the stock of robots per worker, as in Acemoglu and Restrepo (2018) and restrict the sample to 2004 and onwards, when the adoption of robots becomes non-zero. The coefficient of interest is α_4. It captures the differential effect of the routine task content index RTC as technology adoption evolves over time at the country level. This specification allows us to test in what way the effect of RTC on labor market outcomes changes over time, reflecting changes in availability, quality and price of technology.

Results support our previous findings, while the larger number of observations and variability in the exposure to automation allows us to achieve smaller confidence intervals for the estimates. Table 6 shows the results. As technology adoption accelerates, employment decreases in industries with high RTC index and wages increase. The effect on wages is statistically significant in three out of six definitions of the RTC index. The net effect on the labor share is not large enough to be statistically different from zero.

Both empirical strategies show that, as expected from our premise, workers in industries with a high degree of routinization are negatively affected as employment is reduced, a finding that is consistent with the idea that routine tasks are more prone to being replaced by automation technology. The individuals who remain employed, however, enjoy higher

Table 6: Industry-Level Regressions: Parameterization of Technology Adoption

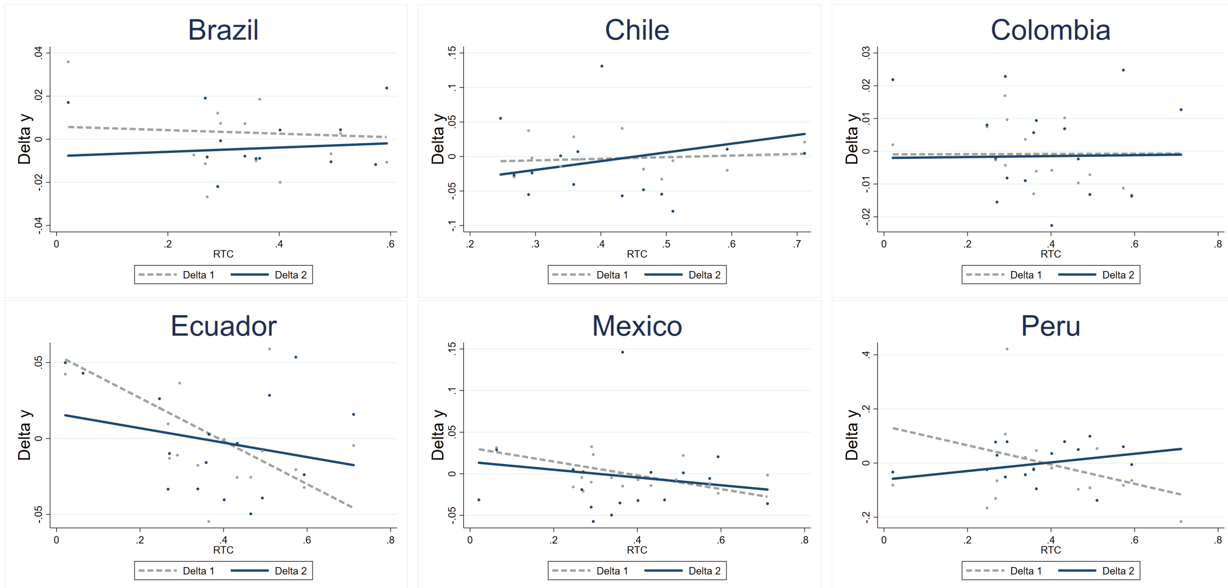
	Log employment	Log wage	Labor share
	(1)	(2)	(3)
RTC1			
$RTC \times Tech$	-0.51	0.17	-0.01
	(0.18***)	(0.07**)	(0.02)
RTC2			
$RTC \times Tech$	-0.65	0.21	-0.02
	(0.35*)	(0.12*)	(0.04)
RTC3			
$RTC \times Tech$	-0.25	0.06	-0.01
	(0.11**)	(0.05)	(0.01)
RTC4			
$RTC \times Tech$	-0.26	0.06	-0.02
	(0.12**)	(0.05)	(0.02)
RTC5			
$RTC \times Tech$	-0.82	-0.08	-0.01
	(0.15***)	(0.09)	(0.02)
RTC6			
$RTC \times Tech$	-0.38	0.10	0.00
	(0.15**)	(0.06*)	(0.02)
Obs.	729	711	711

Notes: Dependent variables are: industry log employment, industry log average wage, industry share of labor. Table shows coefficients α_4 from regression equation (5). Regressions control for initial labor share, initial log value added per worker, and change in log value added per worker. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

wages. This is explained by the increase in productivity brought about by technology and also by selection, as workers who remain employed are those who are better able to work in ways complementary with technology. The strategy based on annual data given by equation (5) confirms that the effects on labor market outcomes are indeed monotonic in technology adoption.

The effects of technology adoption in the labor share need not be the same across countries. In order to estimate heterogeneous effects, we run regressions (3) and (4) separately for each country. One important caveat is that the number of observations is small at the

Figure 2: Labor Share



Notes: Graph plots regression results from (3) and (4) run separately for each country. Dependent variable: industry share of labor. Lines represent the conditional expectations of the outcome variables as a function of the routine task content index. Their slopes represent the coefficients α_1 and α_2.

country level; as a result, the standard errors are large and most estimates are not statistically significant. However, the point estimates allow us to grasp differences in trends across countries. Results from index RTC_1 are plotted in Figure 2. The data points plot the RTC_1 index in the horizontal axis and changes in the labor share in the vertical axis. The lines represent expectations (fitted values) of the changes in the labor share conditional on the RTC index.[13] The slope of the dashed line is the coefficient α_1, while the slope of the solid line is the coefficient α_2.

In the second time period (α_2), the effect of RTC on the labor share is positive for Brazil, Chile, and Peru; it is negative for Ecuador and Mexico; and it is close to zero for Colombia. There are no data available from UNIDO for Argentina in the third time period t_2, which prevents us from computing the second difference.

To sum up, whereas the adoption of technology may have a negative impact on the labor share through the substitution of workers by machines, it may simultaneously have a positive

[13] The changes in the labor share are purged of covariates in a previous step, so that the graphs control for these variables and represent exactly equation regressions (3) and (4).

impact through an increase in the wages of surviving workers as they become complementary with new technologies and productivity is boosted at the firm level. Our findings show that employment indeed falls for workers in industries with high routine task content index and that wages weakly increase. The net effect on the labor share is estimated to be close to zero.

3.1 Worker Mobility across Industries

In industries with a high RTC index, workers are more likely to be displaced by technology, as shown in the previous section. Displaced workers may remain unemployed, or they may switch to other industries. To study worker turnover we define the share of each industry in total manufacturing employment, from UNIDO data, and we work with an empirical strategy analogous to the one in the previous section.

We uncover three important empirical findings, shown in Table 7. First, column (1) reports the correlation between the *level* of the industry share in employment and the RTC index *for the year 2005*. The correlation is positive and significant, implying that industries with a higher percentage of routinary tasks explain larger shares of employment. This is an important finding because it implies that there is high scope for workers switching out of high-RTC industries.

Second, in the year 2013 (column 2), the correlation becomes weaker, as automation technology becomes more prevalent and workers flow to other industries. This second finding, about the change in share, is formally tested using the same empirical strategy as in equations (3) and (4). Results are in Table 7 columns (3) and (4), with the *change* in the share in employment as dependent variable. Between t_2 and t_1 (column 4, the second difference), there is a negative effect of RTC on industry share in employment. A 10 percentage point difference in routinization across industries is associated with a relative decrease in industry share of 2.7, 4.7, 2.8, 4.2, 0.8 and 0.2, respectively, according to the different definitions of the RTC index. No similar changes in share occur between t_1 and t_0 (column 3). This finding

Table 7: Industry-Level Regressions: Share of Industry in Total Employment and Output

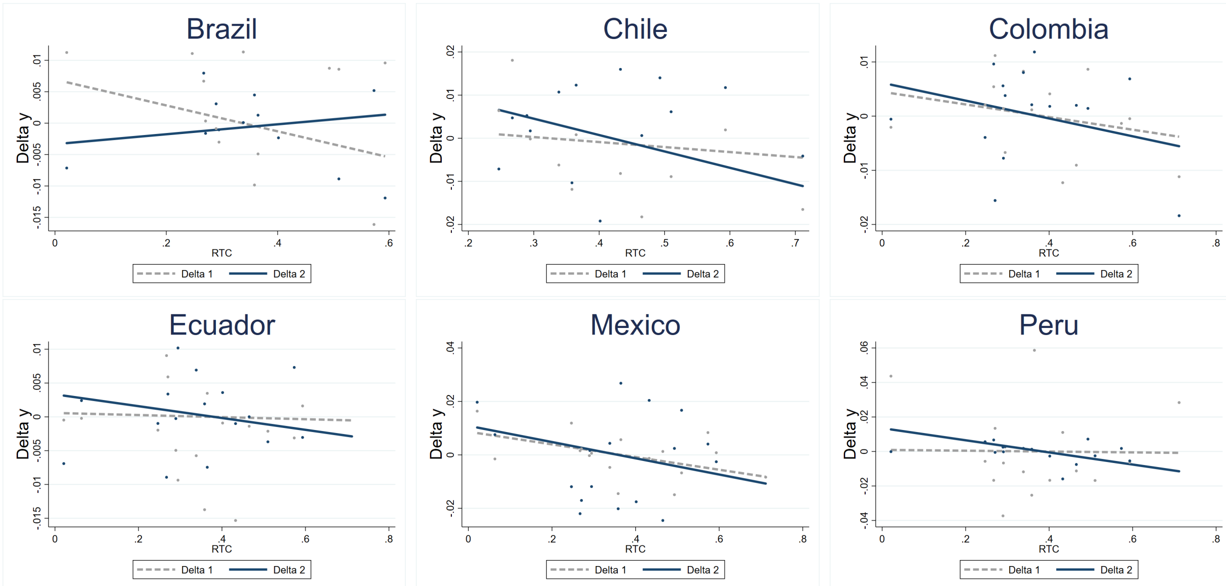
	Share in employment		Share in employment		Share in output	
	2005	2013	Δ_1	Δ_2	Δ_1	Δ_2
	(1)	(2)	(3)	(4)	(5)	(6)
RTC1						
	0.214	0.131	0.012	-0.027	0.015	-0.008
	(0.06***)	(0.04***)	(0.01)	(0.01***)	(0.01)	(0.01)
RTC2						
	0.135	0.059	-0.004	-0.047	0.008	-0.013
	(0.06**)	(0.05)	(0.02)	(0.02***)	(0.02)	(0.01)
RTC3						
	0.254	0.166	0.021	-0.028	0.019	-0.009
	(0.07***)	(0.05***)	(0.02)	(0.01**)	(0.01)	(0.01)
RTC4						
	0.256	0.163	0.012	-0.042	0.015	-0.013
	(0.08***)	(0.05***)	(0.02)	(0.02**)	(0.02)	(0.01)
RTC5						
	0.052	0.031	0.005	-0.008	0.003	-0.002
	(0.02**)	(0.02*)	(0.00)	(0.00**)	(0.00)	(0.00)
RTC6						
	0.338	0.252	0.071	-0.002	0.066	-0.009
	(0.08***)	(0.07***)	(0.03**)	(0.02)	(0.03**)	(0.01)
Obs.	69	93	118	102	118	102

Notes: In columns (1) and (2) the dependent variable is industry share in total employment for the years 2005 and 2013. Independent variable: routine task content index. Regressions control for country effects. Columns (3) to (6) are analogous to Table 5 with dependent variables industry share in total employment and industry share in total output. Regressions control for initial labor share, initial log value added per worker, and change in log value added per worker. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

supports the idea that workers are displaced from high *RTC* industries due to automation.

The third finding relates to the change in industry share in manufacturing output and it is reported in Table 7, columns (5) and (6). Between t_2 and t_1 (column 6, the second difference) point estimates suggest that there is a decrease in the share in output of industries with high RTC index. These results are small in magnitude (compared to column 4) and not statistically significant and we must interpret them with caution. Industries with high RTC index are, as we have shown in columns 1 and 2 of this same table, more intensive in

Figure 3: Share of Industry in Total Employment



Notes: Notes: Analogous to Figure 2 with outcome variable: share of industry in total employment.

labor and less technologically oriented. Workers perform routinary tasks and are less prone to work in complement with technology, meaning that the gains from automation could be lower than in low-RTC industries. As automation technology becomes available, high-RTC industries may find it less profitable to adopt it (relative to low RTC industries), which in turn means that their share in output may fall, as well as they labor demand, as they cannot fully take advantage of technological progress. This is an additional channel for worker turnover out of high-RTC industries.

Summing up, workers may leave high-RTC industries for two reasons: i) because in high-RTC industries workers perform routinary tasks and are therefore more easily replaced by machines, and ii) because high-RTC industries are not able to take full advantage of growth opportunities derived from availability of automation technology. Column (6) provides mild support for the second channel, while the difference between column (4) and column (6), with estimates in column (4) that are significant and larger in magnitude than estimates in column (6), provides support for the first channel. The two channels are complementary. The key point is that low-RTC industries are able to adopt automation technology without displacing workers and taking full advantage of productivity gains because workers are complementary with technology, whereas high-RTC industries need to displace workers in order to adopt automation technology.

In Figure 3 we look at industry share in total employment at the country level. Results confirm that, in all countries with the exception of Brazil, workers indeed flow out of industries with high RTC in the second time period.

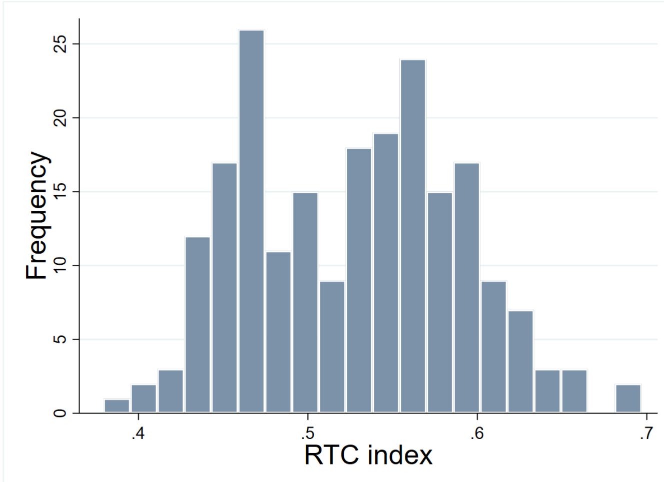
4 Employment and Inequality in Local Labor Markets

In this section we estimate the effects of automation on total employment, unemployment, income, and inequality. These questions require looking at local labor markets in order to have a definition of employment rate, local wages, poverty rate and dispersion in income. We assume that labor mobility is limited across districts within a country, and we define outcome variables for local labor markets. The analysis is based on data from household surveys. There are a total of 214 districts in the seven countries, for an average of 31 districts per country.

Notice that the importance of working with local labor markets is that it allows us to consider general equilibrium effects that work at the local level. That is, this approach allows us to take into consideration that, within a region, there might be mobility of workers across firms, occupations and industries. Workers that lose their job to technology but are able to find a new one either at a new firm, new occupation, or new industry will be employed. Our estimates show the overall equilibrium effect on total regional employment. By contrast, the employment rate cannot be defined by industry or occupation, as by definition only employed workers belong to an industry or occupation.

We exploit the fact that the occupational structure varies across regions. We define an

Figure 4: Dispersion of RTC Index across Districts



Notes: Histogram shows the frequency distribution of the RTC index across districts for the initial time period.

index of routine task content at the regional level given by

$$RTC_r = \sum_i \omega_{ir} RTC_i \tag{6}$$

where RTC_i is the occupation-level index defined in equation (1) and ω is the share of occupation i in total employment of district r in the initial year of data. The RTC_i index is computed from the PIAAC surveys in definitions 1 to 5, and is the index from Autor and Dorn (2013) in definition 6. The shares ω are computed from household surveys. Regional-level indexes vary at the district-country level, with differences in the shares ω.

Figure 4 shows the dispersion of the RTC index across districts. Differences in the RTC index represent the fact that districts differ in the tasks that workers perform. This in turn implies that workers are differently affected by technology adoption, with workers performing routine tasks being more at risk of facing a reduction in labor demand. Figure B1 in Appendix B shows that there is substantial variation in the RTC index not only for the pooled sample of all countries, but also within countries.

Our empirical strategy is analogous to regression equations (3) and (4) from the previous section. The baseline regressions are

$$\Delta y_{rt1} = \mu_1 + \phi_1 RTC_r + x'_{rt0}\zeta_1 + \Delta\epsilon_{rt1} \quad (7)$$

$$\Delta y_{rt2} = \mu_2 + \phi_2 RTC_r + x'_{rt0}\zeta_2 + \Delta\epsilon_{rt2}. \quad (8)$$

As before, we split the data into three time periods: $t_0 = 1992 - 1998$, $t_1 = 1999 - 2004$, and $t_2 = 2005 - 2015$. In the first regression, the changes Δ are computed for the time peridos t_1 and t_0, whereas in the second regression, the changes Δ are computed for the time periods t_2 and t_1. The outcome variables are defined at the district level. The outcome variables are employment, unemployment, hourly wage, labor income, and labor informality. The variables x_0 are district-level controls based on the initial period of data that capture differences in trends across districts.

The coefficients of interest are ϕ_1 and ϕ_2. They capture the correlation between routine task content and the change in the outcome variables. The routine task content index is defined at the district level according to equation (6). We keep the RTC index fixed at its value computed with weights from the initial year of data to minimize endogeneity concerns and to avoid biases from compositional changes.

Table 8 shows results for employment and unemployment. Both variables are defined as rates, that is, the proportion of employed and unemployed individuals in the district. The variables are not complements, as employment is defined over the total population of working age and unemployment is defined over the subpopulation of individuals of working age who are actively working or looking for a job. Columns (2) and (4) show the effect of RTC between t_1 and t_2, after the acceleration in adoption of automation technology that starts in 2005. A high routinization task content index is associated with a decrease in employment and an increase in unemployment. All estimates are large in magnitude and statistically significant. An increase of 10 percentage points in the RTC index is associated to decreases of 1.7, 1.9, 2.5, 2.7, 0.9 and 2.5 points in the employment rate. The effects

Table 8: District-Level Regressions: Employment

	Employment rate		Unemployment Rate	
	Δ_1	Δ_2	Δ_1	Δ_2
	(1)	(2)	(3)	(4)
RTC1				
	-0.04	-0.17	-0.01	0.15
	(0.03)	(0.04***)	(0.03)	(0.03***)
RTC2				
	-0.03	-0.19	0.01	0.14
	(0.04)	(0.04***)	(0.03)	(0.03***)
RTC3				
	-0.07	-0.25	-0.02	0.23
	(0.05)	(0.07***)	(0.04)	(0.05***)
RTC4				
	-0.06	-0.27	-0.01	0.23
	(0.05)	(0.06***)	(0.04)	(0.05***)
RTC5				
	-0.02	-0.09	-0.01	0.08
	(0.02)	(0.02***)	(0.01)	(0.02***)
RTC6				
	-0.11	-0.25	-0.04	0.25
	(0.05**)	(0.07***)	(0.04)	(0.05***)
Obs.	161	207	161	207

Notes: Dependent variables are: columns (1) and (2) district employment rate, columns (3) and (4) district unemployment rate. Table shows coefficients ϕ_1 and ϕ_2 from regression equations (7) and (8). Columns (1), (3) refer to changes in outcome defined as $t_1 - t_0$. Columns (2), (4) refer to changes in outcome defined as $t_2 - t_1$. Regressions control for initial average wage and employment rate. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

on the unemployment rate are increases of 1.5, 1.4, 2.3, 2.3, 0.8 and 2.5 percentage points. In contrast, columns (1) and (3) show virtually no large and significant changes between t_0 and t_1. These results support the idea that in districts in which individuals tend to perform routine tasks, they are more likely to lose their jobs due to the adoption of automation technology that occurs after 2005.

We now turn to job characteristics. Table 9 shows the effects of the RTC index on the

Table 9: District-Level Regressions: Wages

	Log wage		Informality rate	
	Δ_1	Δ_2	Δ_1	Δ_2
	(1)	(2)	(3)	(4)
RTC1				
	-0.57	0.85	0.05	-0.25
	(0.32*)	(0.40**)	(0.06)	(0.09***)
RTC2				
	-0.30	0.86	0.03	-0.11
	(0.23)	(0.32***)	(0.07)	(0.09)
RTC3				
	-1.00	1.25	0.09	-0.41
	(0.66)	(0.74*)	(0.09)	(0.17**)
RTC4				
	-0.73	1.23	0.07	-0.30
	(0.48)	(0.64*)	(0.09)	(0.13**)
RTC5				
	-0.29	0.42	0.03	-0.12
	(0.19)	(0.24*)	(0.03)	(0.05**)
RTC6				
	-0.58	0.71	-0.05	-0.22
	(0.46)	(0.50)	(0.09)	(0.12*)
Obs.	161	207	161	207

Notes: Analogous to Table 8 with outcome variables: columns (1) and (2): Log average wage; columns (3) and (4): Informality rate. Regressions control for initial average wage and employment rate. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

average hourly wage and the informality rate, both at the district level.[14] Average wages are increasing in the RTC index between t_2 and t_1. A difference of 10 percentage points in the routinization index across districts is associated with increases in wages of 8.5, 8.6, 12.5, 12.3, 4.2 and 7.1 percentage points, respectively. Informality is decreasing in the RTC index in magnitudes of 2.5, 1.1, 4.1, 3.0, 1.2 and 2.2 percentage points for a 10 percentage point difference in RTC. These results complement the findings on the increase in unemployment. Workers that remain employed enjoy higher income and higher formality rates. This occurs

[14]The average wage is the average labor income divided by the average number of hours worked.

because of the increase in productivity due to technology adoption, and due to selection of workers. The most productive workers who are able to work in complement with technology remain employed. No significant results are found for the difference between t_0 and t_1.[15]

Similar results for both employment and job quality are obtained when we use a regression specification analogous to (5) with annual data and where $Tech$ is the country-level stock of robots per worker. Results are in Table 10. Adoption of automation technology is associated with a decrease in employment, an increase in the average wage, and a decrease in the informality rate. Effects on unemployment are not statistically significant in this specification.

Results vary by country. Figure 5 shows that employment is decreasing due to automation in Argentina, Brazil and Mexico, while wages are increasing in Brazil, Chile, Peru, and virtually unchanged in Argentina and Mexico. We exclude Colombia and Ecuador from country-level regressions because of lack of data for several years at the beginning of the sample.

To sum up, results in this section show a strong heterogeneity in the effects of automation. While some workers are displaced from the labor market due to automation technology, surviving workers enjoy higher income and formality conditions. There is an increase in unemployment and at the same time an increase in job quality based on increases in productivity and selection.

4.1 Effects on Poverty and Inequality

Results from the previous section indicate that some workers face gains from automation, while other workers suffer losses. The increase in wages and the decrease in informality based on selection suggest that workers at the bottom of the skill and income distribution might be the most vulnerable to being displaced, which in turn has negative effects on income distribution and poverty. In this section we start by studying the unemployment rate across

[15] Similar results (not shown) are found when we work with total labor income instead of the hourly wage.

Table 10: District-Level Regressions: Parameterization of Technology Adoption

	Employment rate	Unemployment rate	Wage	Informality rate
	(1)	(2)	(3)	(4)
RTC1				
$RTC \times Tech$	-0.122	0.001	1.512	-0.330
	(0.019***)	(0.016)	(0.208***)	(0.046***)
RTC2				
$RTC \times Tech$	-0.202	0.012	2.235	-0.576
	(0.031***)	(0.024)	(0.329***)	(0.076***)
RTC3				
$RTC \times Tech$	-0.075	-0.004	1.035	-0.207
	(0.013***)	(0.011)	(0.141***)	(0.031***)
RTC4				
$RTC \times Tech$	-0.082	-0.004	1.100	-0.228
	(0.014***)	(0.012)	(0.154***)	(0.034***)
RTC5				
$RTC \times Tech$	-0.224	0.035	1.971	-0.547
	(0.031***)	(0.023)	(0.302***)	(0.077***)
RTC6				
$RTC \times Tech$	-0.110	-0.004	1.443	-0.305
	(0.018***)	(0.015)	(0.203***)	(0.044***)
Obs.	548	548	548	548

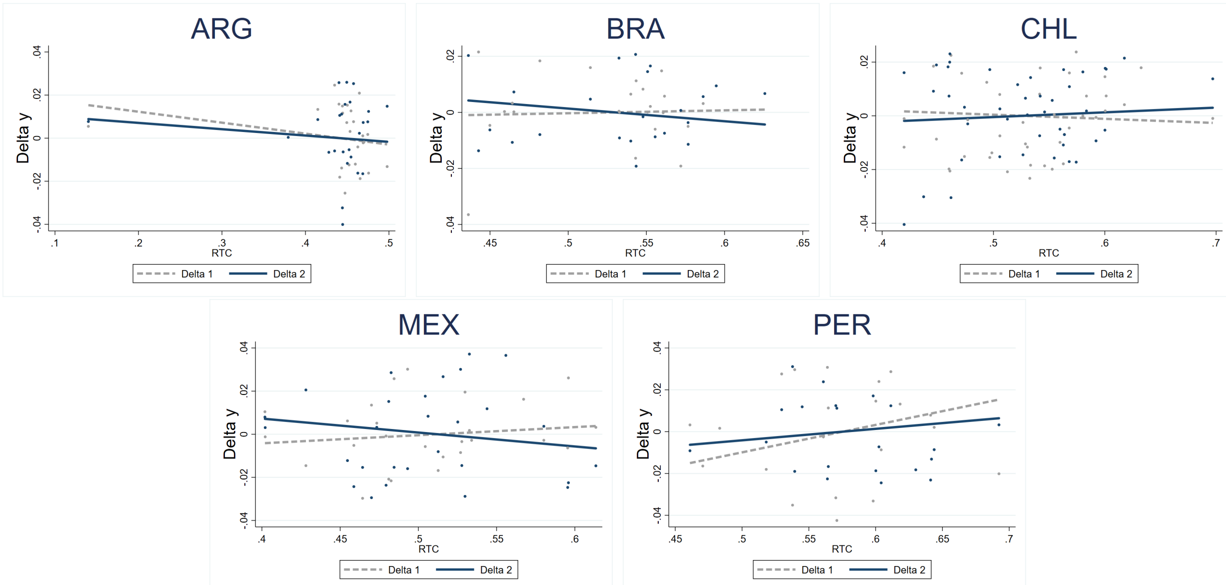
Notes: Dependent variables are: Employment rate, unemployment rate, log district average wage, informality rate. Regressions control for initial average wage and employment rate. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

different levels of skill, and then turn to measures of inequality and poverty, all defined at the district level.

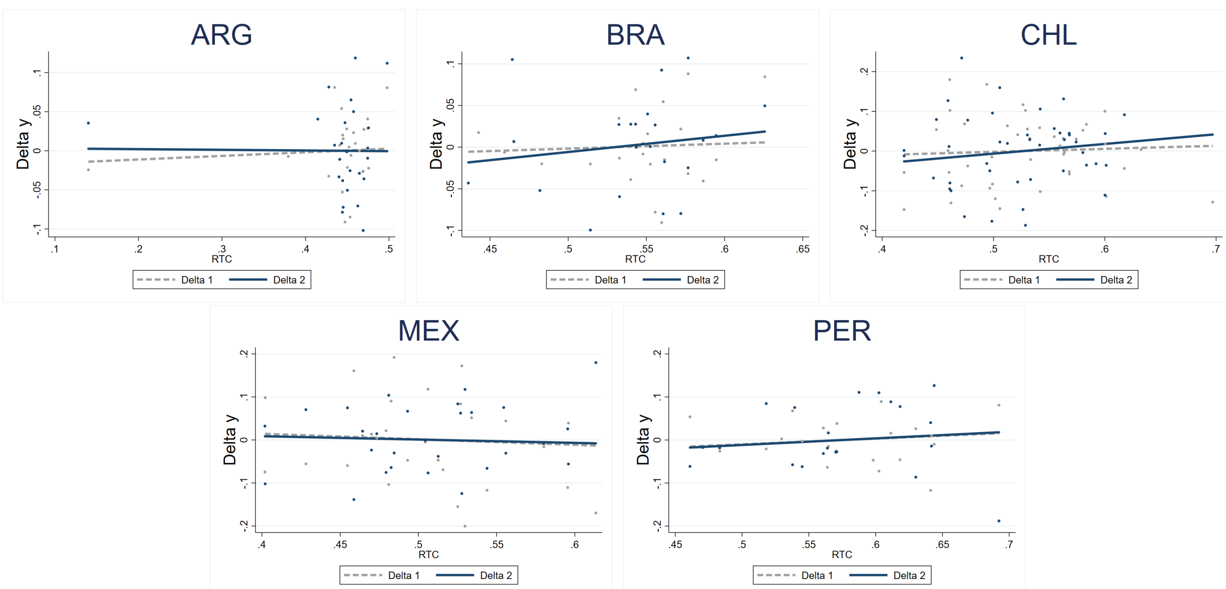
We split workers into three skill groups: unskilled workers, defined as those workers with no high school degree; skilled workers, defined as workers with a high school degree and no further education; and highly skilled workers, defined as those with tertiary education or a college degree. We compute the unemployment rate for each skill group at the district level and run linear regressions (7) and (8) separately for each group. Results are in Table 11. The table shows that for the second difference in outcomes, between t_2 and t_1 (columns 2,

Figure 5: Employment and Wages

(a) District employment rate



(b) District average wage



Notes: Analogous to Figure 2 with outcome variables: employment at the district level, average wage at the district level.

4, 6), a higher RTC index is associated to increases in unemployment for each skill group. Furthermore, the increase is largest for unskilled workers and lowest for highly skilled workers. Results are statistically significant for all definitions of the RTC index.

As an additional test, we adopt a flexible specification in which we compute a time-

Table 11: District-Level Regressions: Unemployment by Skill Groups

	Unskilled		Skilled		Highly skilled	
	Δ_1	Δ_2	Δ_1	Δ_2	Δ_1	Δ_2
	(1)	(2)	(3)	(4)	(5)	(6)
RTC1						
	-0.03	0.17	-0.06	0.13	-0.01	0.11
	(0.03)	(0.04***)	(0.07)	(0.04***)	(0.03)	(0.03***)
RTC2						
	-0.01	0.16	-0.06	0.14	0.00	0.12
	(0.03)	(0.03***)	(0.09)	(0.03***)	(0.03)	(0.03***)
RTC3						
	-0.06	0.27	-0.09	0.20	-0.03	0.17
	(0.05)	(0.06***)	(0.11)	(0.06***)	(0.04)	(0.05***)
RTC4						
	-0.04	0.27	-0.09	0.22	-0.02	0.18
	(0.05)	(0.05***)	(0.11)	(0.05***)	(0.04)	(0.05***)
RTC5						
	-0.02	0.10	-0.03	0.08	-0.01	0.06
	(0.02)	(0.02***)	(0.04)	(0.02***)	(0.01)	(0.02***)
RTC6						
	-0.06	0.29	-0.10	0.24	-0.04	0.16
	(0.04)	(0.06***)	(0.10)	(0.06***)	(0.04)	(0.05***)
Obs.	161	207	161	207	161	207

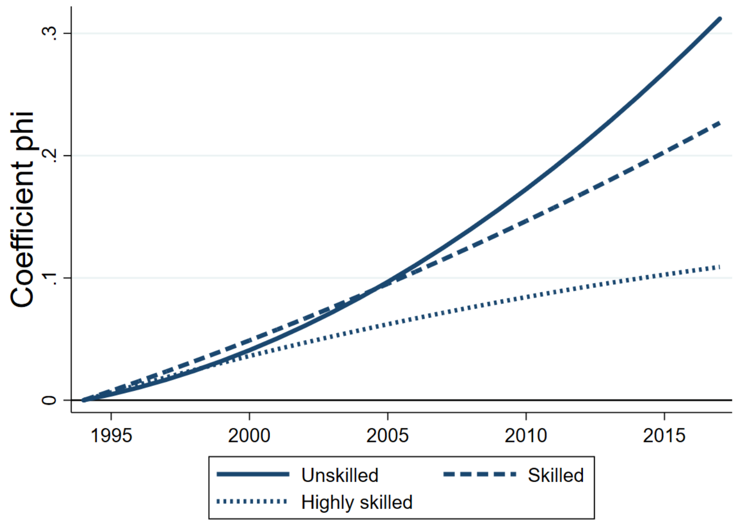
Notes: Dependent variable: unemployment rate computed for three skill groups. Unskilled workers: no high school degree. Skilled workers: high school degree and no further education. Highly skilled workers: tertiary education or university degree. Table shows coefficients ϕ_1 and ϕ_2 from regression equations (7) and (8). Columns (1), (3), (5) refer to changes in outcome defined as $t_1 - t_0$. Columns (2), (4), (6) refer to changes in outcome defined as $t_2 - t_1$. Regressions control for initial average wage and employment rate. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

varying coefficient $\phi(t)$ to estimate the effect of RTC on unemployment of different skill groups. The regression equation is given by

$$\widetilde{\Delta} y_{jt} = \mu_3 + \widetilde{\phi}(t) RTC_j + \widetilde{\Delta} x'_{jt} \theta_3 + x'_{jt0} \zeta_3 + \widetilde{\Delta} \epsilon_{jt}. \tag{9}$$

The coefficient of interest ϕ, instead of taking two values ϕ_1 and ϕ_2 as in regressions (7) and (8), is an unknown function of time, reflecting the variability in availability and cost of

Figure 6: District-Level Regressions: Unemployment, Graphical Representation



Notes: Dependent variable: unemployment rate. Coefficient $\widetilde{\phi}_(t)$ from polynomial regression equation (9) run separately for each skill group. It represents the time-varying effects of the RTC index on unemployment of each skill group.

technology across the sample years. In the empirical implementation we approximate the function $\widetilde{\phi}$ with a second order polynomial in t. In (9) we use annual data and the variables $\widetilde{\Delta} y_t$ and $\widetilde{\Delta} x_t$ denote changes in y and x computed between t and t_0.

Estimates of the function $\widetilde{\phi}(t)$ are plotted in Figure 6, for index RTC_1. The effect at time t_0 is zero. From that point onwards, the graphs show the cumulative (relative to other industries) change in unemployment between time t_0 and t. A positive value represents a positive cumulative (relative) effect at time t. A positive slope represents an increasing (relative) effect at time t. The solid line depicts the coefficients for the unskilled group, the dashed line plots the coefficients for the skilled group, and the dotted line plots the coefficients for the highly skilled group. Unemployment increases for all groups. The effects are decreasing in skill type, across all years. As expected, the difference in unemployment rates between unskilled and skilled workers accelerates around 2005. This result is only driven by data, as no cutoffs for *pre* and *post* treatment years are imposed in this specification. Unskilled workers are more likely to be displaced by automation technology.

We now turn to direct measures of poverty and inequality. For the poverty rate, we

Table 12: District-Level Regressions: Poverty and Inequality

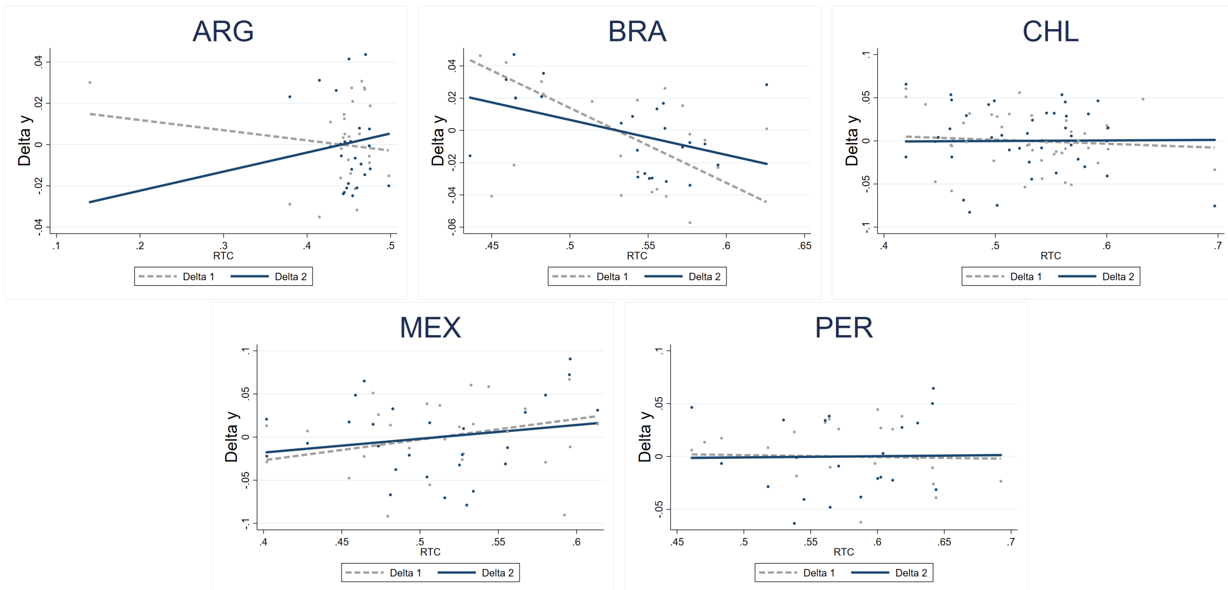
	Poverty rate		Inequality p75–p25	
	Δ_1	Δ_2	Δ_1	Δ_2
	(1)	(2)	(3)	(4)
RTC1				
	-0.01	0.37	-0.76	0.98
	(0.17)	(0.19**)	(0.53)	(0.49**)
RTC2				
	0.01	0.02	-0.48	0.83
	(0.14)	(0.21)	(0.60)	(0.51)
RTC3				
	0.00	0.65	-1.25	1.56
	(0.31)	(0.26**)	(0.76*)	(0.72**)
RTC4				
	-0.08	0.49	-1.23	1.50
	(0.25)	(0.26*)	(0.76)	(0.72**)
RTC5				
	-0.03	0.18	-0.46	0.54
	(0.09)	(0.09**)	(0.26*)	(0.25**)
RTC6				
	-0.21	0.27	-0.75	0.65
	(0.19)	(0.28)	(0.76)	(0.68)
Obs.	161	207	161	207

Notes: Analogous to Table 8 with outcome variables: columns (1) and (2): Poverty rate computed using per capita family income; columns (3) and (4): Poverty rate computed using per capita family income net of transfers. Regressions control for initial poverty rate and interquantile ratio of income. Robust standard errors in parenthesis. Significance at the 1, 5 and 10 percent levels denoted with ***, ** and *.

construct the head count ratio using per capita family income and official poverty lines. For inequality, we compute the ratio between income percentiles 75th and 25th in per capita family income.[16] Table 12 shows results, with columns 2 and 4 reporting the difference between t_2 and t_1. Results support the expectations that workers at the bottom of the income distribution are more affected by technology adoption and that this differential effects are

[16]Similar results (not shown) are obtained when we use different measures of income, poverty lines, and the ratio of income percentiles 90th to 10th. In particular, we experiment with per capita family income net of government transfers, to take into consideration that during our sample period several Latin American countries expanded their social welfare programs. Qualitative results remain unchanged.

Figure 7: Poverty



Notes: Analogous to Figure 2 with outcome variable: poverty head count ratio based on per capita family income.

reflected on distributional variables. A regional difference of 10 percent in the RTC index is associated with increases in the poverty rate of 3.7, 0.2, 6.5, 4.9, 1.8 and 2.7 percentage points, respectively, and increases in income inequality of 9.8, 8.3, 15.6, 15.0, 5.4, 6.5 points, respectively in the income ratio (columns 2 and 4). Results are statistically significant for four out of six definitions of the RTC index. Virtually no significant results are obtained for the pre-automation period, corresponding to the difference between t_1 and t_0 (columns 1 and 3). Figure 7 shows heterogeneous results by country, with poverty rates that are increasing in Argentina, Chile, Mexico and slightly in Peru. An exception is Brazil, with relative decreasing poverty rates in both time periods.

5 Conclusion

Automation has significant impacts on labor markets and welfare. These effects are complex and unequally distributed. First, we find that automation has an effect on employment. Employment decreases in industries and districts with high job routinization content, relative to industries and districts with low job routinization content. It is important to understand that there are general equilibrium effects that are not captured by our empirical strategy. We do not estimate the *level* effect on employment (or unemployment). Our findings show that *relative* employment decreases in industries and districts according to their RTC index. These findings provide very strong support, from the two different perspectives of industries and districts, to the hypothesis that workers performing routine tasks are indeed at a higher risk of being displaced by automation technology.

Our second finding is that wages increase as a result of technology adoption. As discussed above for the effects on employment, our estimates of the effects of automation on wages refer to *relative* effects across industries and districts. As workers are displaced due to investment in automation technology, the more productive workers who are able to work in complement with technology remain employed, with their productivity and wages increased. The selection of workers also leads to a decrease in the informality rate, which occurs at the expense of an increase in the rate of unemployment.

Finally, regarding the distribution of income, we provide two sets of results. We first study changes in the labor share. Because employment falls but wages go up, the labor share does not change significantly. We do not find evidence that the functional distribution of income is significantly affected by automation technology. The personal distribution of income is a different matter. The functional distribution of income involves only employed individuals, while the personal distribution of income includes displaced individuals as well. We find that workers who perform routine tasks are more likely to be displaced by technology. The task content of a job correlates to skills and income, therefore workers at the lower tail of the income distribution are more likely to be negatively affected by automation. We find evidence that automation affects employment of unskilled workers relatively more than employment of skilled and highly skilled workers. That is, unemployment is negatively correlated with skills. We further find that at the district level, *relative* changes in poverty and inequality correlate positively with the routinization index. That is, social welfare variables deteriorate with the acceleration of technology adoption in districts with a high degree of routinization relative to districts with a low degree of routinization.

References

Acemoglu, D., and Restrepo, P. (2018). Robots and jobs: Evidence from US labor markets.

Akerman, A., Gaarder, I., and Mogstad, M. (2015). The skill complementarity of broadband internet. Quarterly Journal of Economics, 130(4), 1781-1824.

Almeida, R., Fernandes, A., and Viollaz, M. (2017). Does the Adoption of Complex Software Impact Employment Composition and the Skill Content of Occupations? Evidence from Chilean Firms. World Bank Policy Research Working Paper No. 8110.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. Quarterly Journal of Economics, 118(4), 1279-1333.

Autor, D. H., and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. American Economic Review, 103(5), 1553-1597.

Autor, D., and Salomons, A. (2018). Is automation labor-displacing? Productivity growth, employment, and the labor share. Brookings Papers on Economic Activity.

Bound, J., and Johnson, G. (1992). Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations. American Economic Review, 82(3), 371-392.

Card, D., and Lemieux, T. (2001). Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis. Quarterly Journal of Economics, 116(2), 705-746.

Das, M. M., and Hilgenstock, B. (2018). The Exposure to Routinization: Labor Market Implications for Developed and Developing Economies. International Monetary Fund.

Dutz, M. A., Almeida, R. K., and Packard, T. G. (2018). The Jobs of Tomorrow: Technology, Productivity, and Prosperity in Latin America and the Caribbean. The World Bank.

Faber, M. (2018). Robots and reshoring: Evidence from Mexican local labor markets.

Goos, M., and Manning, A. (2007). Lousy and lovely jobs: The rising polarization of work in Britain. Review of Economics and Statistics, 89(1), 118-133.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. American Economic Review, 104(8), 2509-2526.

Graetz, G., and Michaels, G. (2018). Robots at Work. Review of Economics and Statistics, forthcoming.

Katz, L. F., and Murphy, K. M. (1992). Changes in Relative Wages, 1963-1987: Supply and Demand Factors. Quarterly Journal of Economics, 107(1), 35-78.

Maloney, W. F., and Molina, C. (2016). Are automation and trade polarizing developing country labor markets, too?. The World Bank.

Michaels, G., Natraj, A., and Van Reenen, J. (2014). Has ICT polarized skill demand? Evidence from eleven countries over twenty-five years. Review of Economics and Statistics, 96(1), 60-77.

Messina, J., and Silva, J. (2017). Wage inequality in Latin America: Understanding the past to prepare for the future. The World Bank.

Spitz-Oener, A. (2006). Technical change, job tasks, and rising educational demands: Looking outside the wage structure. Journal of Labor Economics, 24(2), 235-270.

Appendix A: Data

UNIDO Database

The UNIDO database is the INDSTAT 2 Industrial Statistics Database, available from http://stat.unido.org. The database collects information at the 2-digit level of the ISIC Revision 3 classification. In our empirical analysis we work with this classification, with the caveat that we group together industries 30, 32 and 33 in order to match them to the classification in the PIAAC survey. These industries are "Manufacture of office, accounting and computing machinery," "Manufacture of radio, television and communication equipment and apparatus," "Manufacture of medical, precision and optical instruments, watches and clocks." A list of the 2-digit industries is in Table A2.

The UNIDO database has information on industry-level wage bill, employment and output across countries and across years. We define the labor share as the ratio of wage bill to industry output.

SEDLAC database

SEDLAC is a database of socio-economic statistics constructed from microdata of household surveys from the Latin American and Caribbean (LAC) developed by CEDLAS (Universidad Nacional de La Plata) and the World Bank's LAC poverty group (LCSPP).[17]

We use the SEDLAC database to construct RTC indexes at the country-district level. The surveys have information on occupations at different classification systems. We use concordance tables to match this information with the ISCO 08 classification system used in the PIAAC surveys so that the RTC indexes are comparable across countries. We further construct poverty and inequality indicators, as well as labor market outcomes at the country-district level.

PIAAC Surveys

The PIAAC surveys are the Survey of Adult Skills conducted in several countries by the

[17] http://www.cedlas.econo.unlp.edu.ar/wp/en/estadisticas/sedlac/

OECD as part of the Programme for the International Assessment of Adult Competencies. The surveys are publicly available at the OECD-PIAAC website https://www.oecd.org/skills/piaac/.

We base our index definitions on the following questions:

1. The Supervision task dummy is based on the following two questions. Do you manage or supervise other employees? (Possible answers: 1, 2) (d–q08a). How often does your job usually involve instructing, training or teaching people, individually or in groups? (Possible answers: 1, 2, 3, 4, 5) (f–q02b). The Supervision dummy is defined as positive when the first answer is equal to one, or the second answer is equal to 4 or 5.

2. The Planning task dummy is based on the following question. How often does your job usually involve planning the activities of others? (Possible answers: 1, 2, 3, 4, 5) (f–q03b). The Planning dummy is defined as positive when the answer is equal to 4 or 5.

3. The Problem solving task dummy is based on the following question. How often are you confronted with more complex problems that take at least 30 minutes to find a good solution? The 30 minutes only refers to the time needed to think of a solution, not the time needed to carry it out. (Possible answers: 1, 2, 3, 4, 5) (f–q05b). The Problem solving dummy is defined as positive when the answer is equal to 4 or 5.

4. The Written output task dummy is based on the following two questions. In your job, how often do you write reports? (Possible answers: 1, 2, 3, 4, 5) (g–q02c). In your job, how often do you write articles for newspapers, magazines or newsletters? (Possible answers: 1, 2, 3, 4, 5) (g–q02b). The written output dummy is defined as positive when at least one of the two answers is equal to 4 or 5.

5. The Presentations task dummy is based on the following three questions. How often does your job usually involve making speeches or giving presentations in front of 5

or more people? (Possible answers: 1, 2, 3, 4, 5) (f–q02c). How often does your job usually involve advising people? (Possible answers: 1, 2, 3, 4, 5) (f–q02e). How often does your job usually involve selling a product or selling a service? (Possible answers: 1, 2, 3, 4, 5) (f–q02d). The presentations dummy is defined as positive when at least one of the three answers is equal to 4 or 5.

6. The Budget task dummy is based on the following question. In your job, how often do you calculate prices, costs, or budgets? (Possible answers: 1, 2, 3, 4, 5) (g–q03b). The Budget dummy is defined as positive when the answer is equal to 4 or 5.

The individual level flexibility indexes F_1 and F_3 are based on the first four dummies, while F_2, F_4 and F_5 are based on the six dummies. To construct F_5 we perform a linear combination of the dummies in which the weights are obtained by MLE factor analysis. The weights are 0.245, 0.174, 0.137, 0.264, 0.100. The Cronbach coefficient is 0.6. The aggregation across individuals results in task content indexes RTC_1 to RTC_5. Figure A1 shows that the correlation across aggregate indexes is high. In our empirical analysis we use the five indexes constructed from PIAAC, plus the index constructed from Autor and Dorn (2013) to check for robustness to different definitions.

The PIAAC surveys are available for four Latin American countries: Chile, Ecuador, Mexico, and Peru. We pool together the four surveys to construct the aggregate RTC indexes from individual responses. As a robustness exercise we experiment with RTC indexes computed from the individual surveys of Chile (2014–2015), Ecuador, Mexico and Peru (2017). In the experiment, we construct indexes only for industries and occupations that have a sufficiently large number of observations for the latter four countries, and compute the correlation across indexes computed from different samples. Results are in Table A1. The correlation is high, which supports the procedure of using the pool of four countries to compute the RTC indexes.

To construct the aggregate RTC indexes we first need to match industry and occupations in the PIAAC surveys with industries in the UNIDO database and occupations in the household surveys. The PIAAC survey defines industries according to the ISIC Revision 4 classification. We match this classification with the Revision 3 classification of UNIDO. Regarding occupations, the PIAAC survey uses the ISCO 08 classification at the 4-digit level. In order to have sufficient number of observations both from the PIAAC surveys and the household surveys, we match the PIAAC and household surveys at the ISCO 08 2-digit level. Tables A2 and A3 provide a list of the industries and occupations, the four definitions of the RTC indexes, and the number of industry-level and occupation-level observations in the PIAAC survey used to construct the indexes.

Table A1: Correlation of RTC Indexes Computed from Different Samples

	All Latin American surveys				
	RTC1 (1)	RTC2 (2)	RTC3 (3)	RTC4 (4)	RTC5 (5)
Panel A: Occupation-level index					
Chile	0.95	0.90	0.98	0.97	0.96
Ecuador	0.85	0.91	0.82	0.85	0.75
Mexico	0.98	1.00	0.95	0.98	0.92
Peru	0.90	0.97	0.89	0.92	0.86
Panel B: Industry-level index					
Chile	0.78	0.77	0.79	0.76	0.78
Ecuador	0.86	0.91	0.90	0.85	0.90
Mexico	0.99	0.99	0.98	0.98	0.98
Peru	0.78	0.91	0.82	0.82	0.80

Notes: RTC indexes are computed from different samples at the occupation level (Panel A) and at the industry level (Panel B). Column 1 displays the correlation of RTC_1 computed from surveys of the four Latin American countries pooled together, with the RTC index computed separately from the survey of each of the four Latin American countries. Columns 2, 3, 4 and 5 compute analogous correlations for RTC_2, RTC_3, RTC_4 and RTC_5. To compute the correlations we keep occupations and industries with at least 25 observations for each of the four Latin American countries.

Table A2: Industry-Level RTC Indexes

Industry	RTC1 (1)	RTC2 (2)	RTC3 (3)	RTC4 (4)	RTC5 (5)	RTC6 (6)	Obs. (7)
Food and beverages	0.49	0.23	0.80	0.74	0.21	0.58	448
Textiles	0.71	0.46	0.88	0.84	0.38	0.61	59
Apparel	0.57	0.34	0.85	0.78	0.33	0.61	303
Leather	0.51	0.28	0.80	0.77	0.19	0.61	51
Wood	0.59	0.31	0.86	0.80	0.38	0.63	50
Paper	0.27	0.19	0.63	0.65	-0.14	0.56	31
Printing	0.25	0.12	0.76	0.71	0.08	0.48	47
Coke and petroleum	0.02	0.02	0.33	0.38	-0.93	0.46	12
Chemicals	0.36	0.21	0.71	0.67	-0.06	0.50	87
Rubber and plastics	0.34	0.32	0.65	0.64	-0.13	0.57	55
Other minerals prod.	0.47	0.31	0.78	0.76	0.18	0.56	70
Basic metals	0.40	0.27	0.53	0.56	-0.58	0.56	22
Metal products	0.43	0.19	0.74	0.67	0.02	0.58	154
Machinery and equipment nec	0.27	0.11	0.62	0.63	-0.22	0.53	40
Computers, electronics	0.29	0.29	0.61	0.63	-0.19	0.42	22
Electrical machinery	0.29	0.23	0.75	0.75	0.18	0.51	37
Motor vehicles	0.29	0.21	0.63	0.64	-0.16	0.52	94
Other transport equip.	0.06	0.06	0.58	0.61	-0.58	0.55	15
Furniture	0.36	0.15	0.70	0.62	-0.06	0.63	122

Notes: RTC indexes RTC_1 to RTC_5 are computed from pooled PIAAC surveys as weighted averages of the individual level flexibility indexes F_1 to F_5. They are the same across countries. RTC_6 is computed as a weighted average of the occupation level index of Autor and Dorn (2013), using the occupation shares in industry employment as weights. This index varies across countries together with the occupational structure. The table shows the simple average across countries. Column (7) displays the number of surveyed individuals that report employment in each industry in the PIAAC surveys. Columns (1) to (5) are computed based on the number of observations in the PIAAC surveys in column (7).

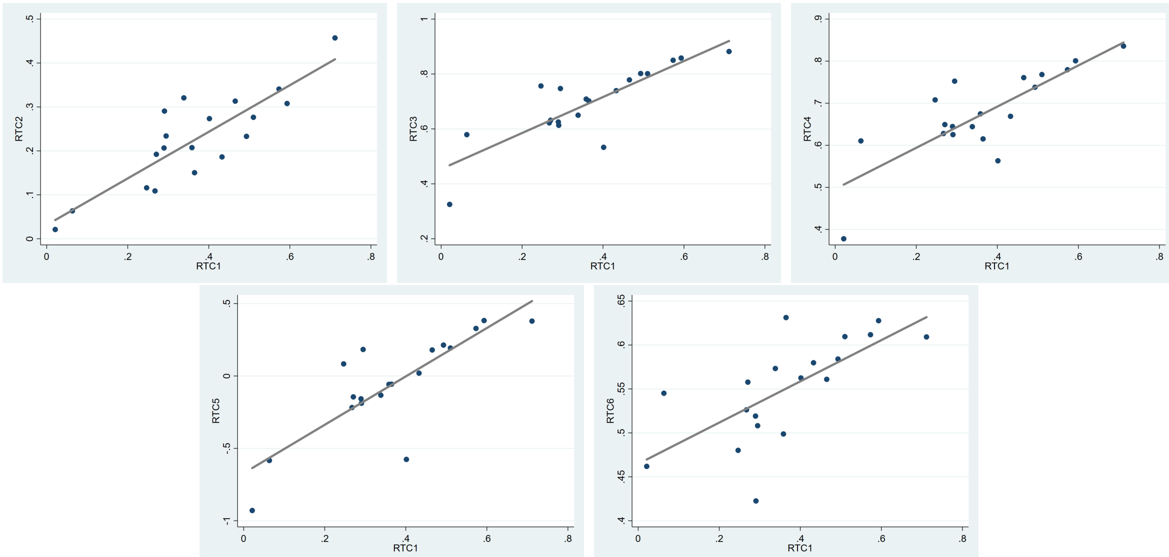
Table A3: Occupation-Level RTC Indexes

Industry	RTC1 (1)	RTC2 (2)	RTC3 (3)	RTC4 (4)	RTC5 (5)	RTC6 (6)	Obs. (7)
Public administration officials	0.18	0.05	0.58	0.49	-0.38	0.17	62
Managers: Administrative	0.05	0.02	0.41	0.37	-0.90	0.19	97
Managers: Production	0.11	0.04	0.46	0.43	-0.69	0.23	235
Managers: Services	0.16	0.03	0.55	0.46	-0.52	0.26	154
Professionals: Science and engineering	0.13	0.06	0.53	0.46	-0.48	0.26	166
Professionals: Health	0.24	0.08	0.67	0.60	-0.04	0.30	190
Professionals: Teaching	0.23	0.04	0.66	0.60	-0.10	0.28	553
Professionals: Business	0.14	0.07	0.57	0.50	-0.26	0.25	260
Professionals: ICT	0.11	0.05	0.53	0.50	-0.40	0.19	50
Professionals: Legal, social, cultural	0.24	0.16	0.63	0.58	-0.14	0.23	206
Associate Prof: Science and engineering	0.15	0.09	0.55	0.54	-0.47	0.44	309
Associate Prof: Health	0.26	0.17	0.69	0.67	0.03	0.49	194
Associate Prof: Business	0.26	0.07	0.65	0.56	-0.09	0.38	459
Associate Prof: Legal, social, cultural	0.21	0.09	0.69	0.58	-0.07	0.36	107
Technicians: ICT	0.14	0.09	0.59	0.56	-0.29	0.34	81
Clerks: General	0.26	0.13	0.66	0.61	-0.11	0.51	147
Clerks: Customer service	0.33	0.07	0.74	0.63	0.12	0.45	212
Clerks: Data	0.28	0.15	0.66	0.60	-0.11	0.57	345
Clerks: Other	0.38	0.23	0.73	0.69	0.09	0.52	119
Workers: Personal service	0.55	0.17	0.84	0.73	0.22	0.46	722
Workers: Sales	0.49	0.09	0.81	0.66	0.23	0.48	1911
Workers: Personal care	0.47	0.36	0.80	0.78	0.22	0.52	210
Workers: Protective service	0.22	0.17	0.65	0.68	-0.04	0.43	316
Workers: Agriculture	0.73	0.55	0.91	0.87	0.45	0.61	673
Workers: Forestry, Fishery, Hunting	0.65	0.21	0.91	0.81	0.40	0.60	58
Workers: Subsistence primary sector	0.75	0.58	0.93	0.88	0.49	0.74	148
Workers: Building and related trades	0.50	0.27	0.80	0.73	0.16	0.68	597
Workers: Metal and machinery	0.37	0.17	0.74	0.66	0.07	0.58	377
Workers: Handicraft and printing	0.57	0.30	0.84	0.78	0.25	0.56	126
Workers: Electrical and electronic trades	0.28	0.09	0.65	0.60	-0.04	0.52	151
Workers: Crafts	0.59	0.26	0.87	0.78	0.37	0.65	574
Plant and machine operators	0.45	0.31	0.80	0.79	0.28	0.70	262
Assemblers	0.44	0.32	0.80	0.81	0.29	0.66	42
Drivers and mobile plant operators	0.62	0.27	0.86	0.78	0.37	0.54	846
Cleaners and helpers	0.76	0.64	0.92	0.90	0.47	0.62	787
Laborers: Agriculture, forestry, fishing	0.77	0.64	0.93	0.91	0.52	0.69	388
Laborers: Mining, const., manuf., transp.	0.68	0.52	0.88	0.85	0.41	0.77	486
Food preparation assistants	0.64	0.16	0.88	0.75	0.33	0.87	258
Street sales and service workers	0.64	0.15	0.90	0.74	0.43	0.41	112
Elementary workers	0.65	0.43	0.88	0.84	0.42	0.57	178

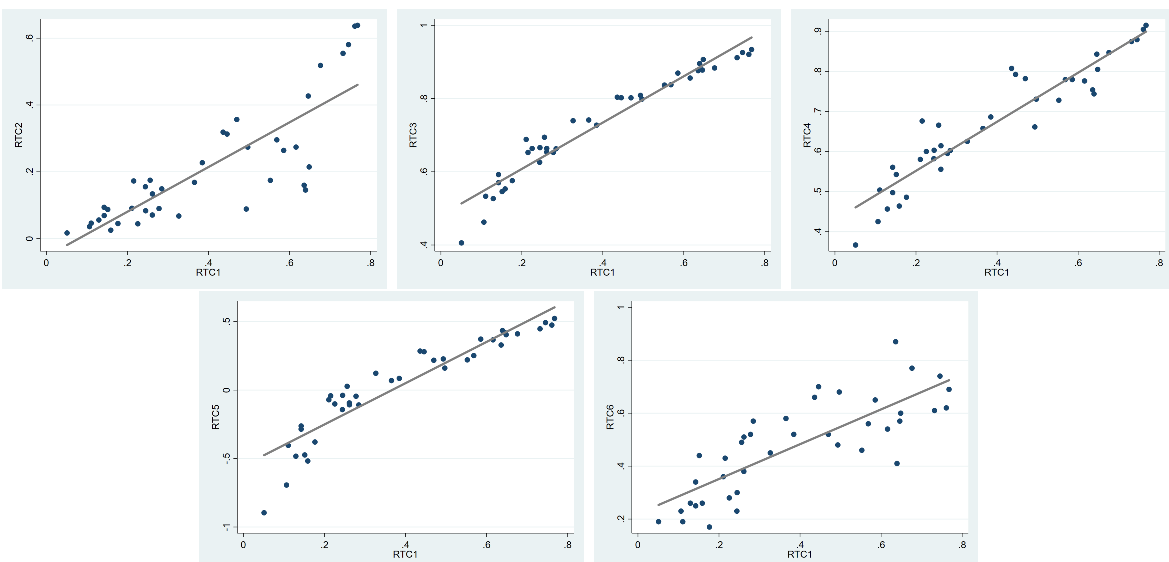
Notes: RTC indexes RTC_1 to RTC_5 are computed from pooled PIAAC surveys as weighted averages of the individual-level flexibility indexes F_1 to F_5. RTC_6 is the occupation-level index of Autor and Dorn (2013). All indexes are the same across countries. Column (7) displays the number of surveyed individuals that report employment in each occupation in the PIAAC surveys. Columns (1) to (5) are computed based on the number of observations in the PIAAC surveys in column (7).

Figure A1: Correlation of Definitions of RTC Indexes

(a) Industry indexes



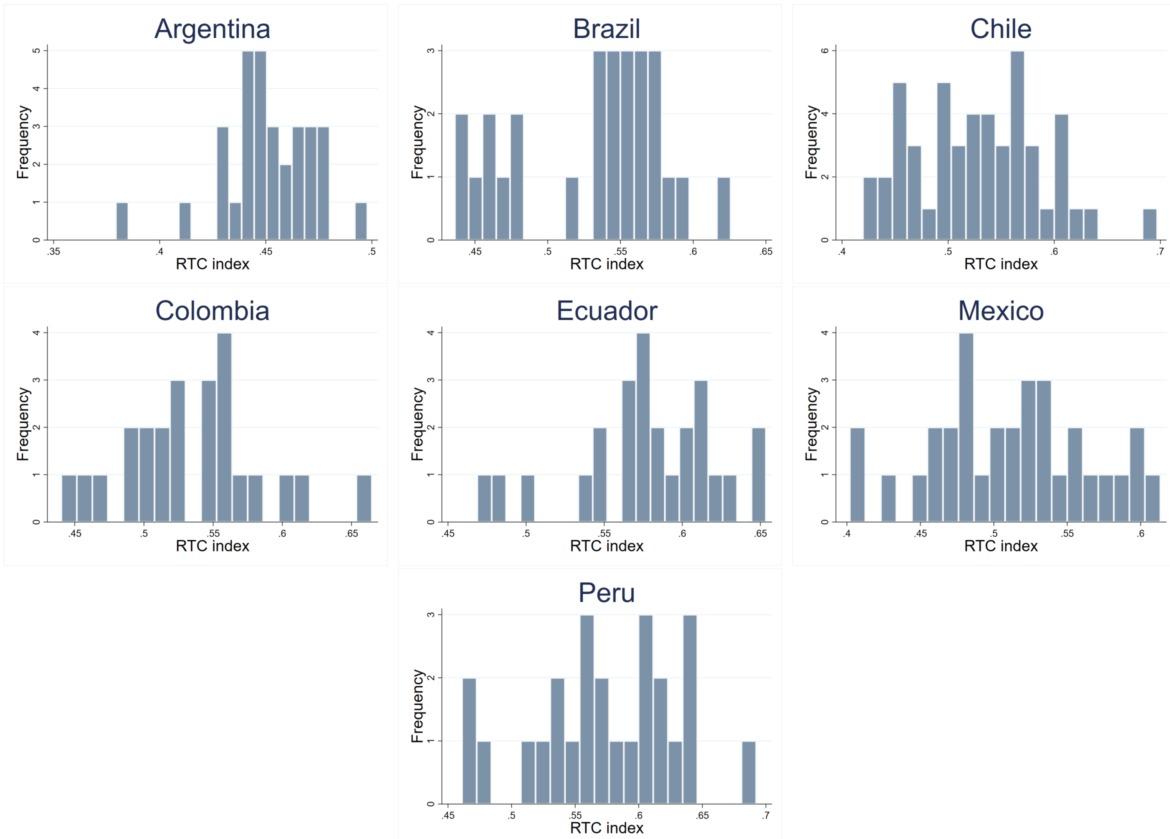
(b) Occupation indexes



Notes: Figure plots the correlation between industry-level indexes RTC_1 and RTC_2 to RTC_6 (top panel), and the correlation between occupation-level indexes RTC_1 and RTC_2 to RTC_6 (bottom panel). Indexes RTC_1 to RTC_5 are computed from the pooled PIAAC surveys, whereas RTC_6 is computed from the index of Autor and Dorn (2013).

Appendix B: Figures and Tables

Figure B1: Dispersion of RTC Index across Districts



Notes: Histograms show the frequency distribution of the RTC index across districts.