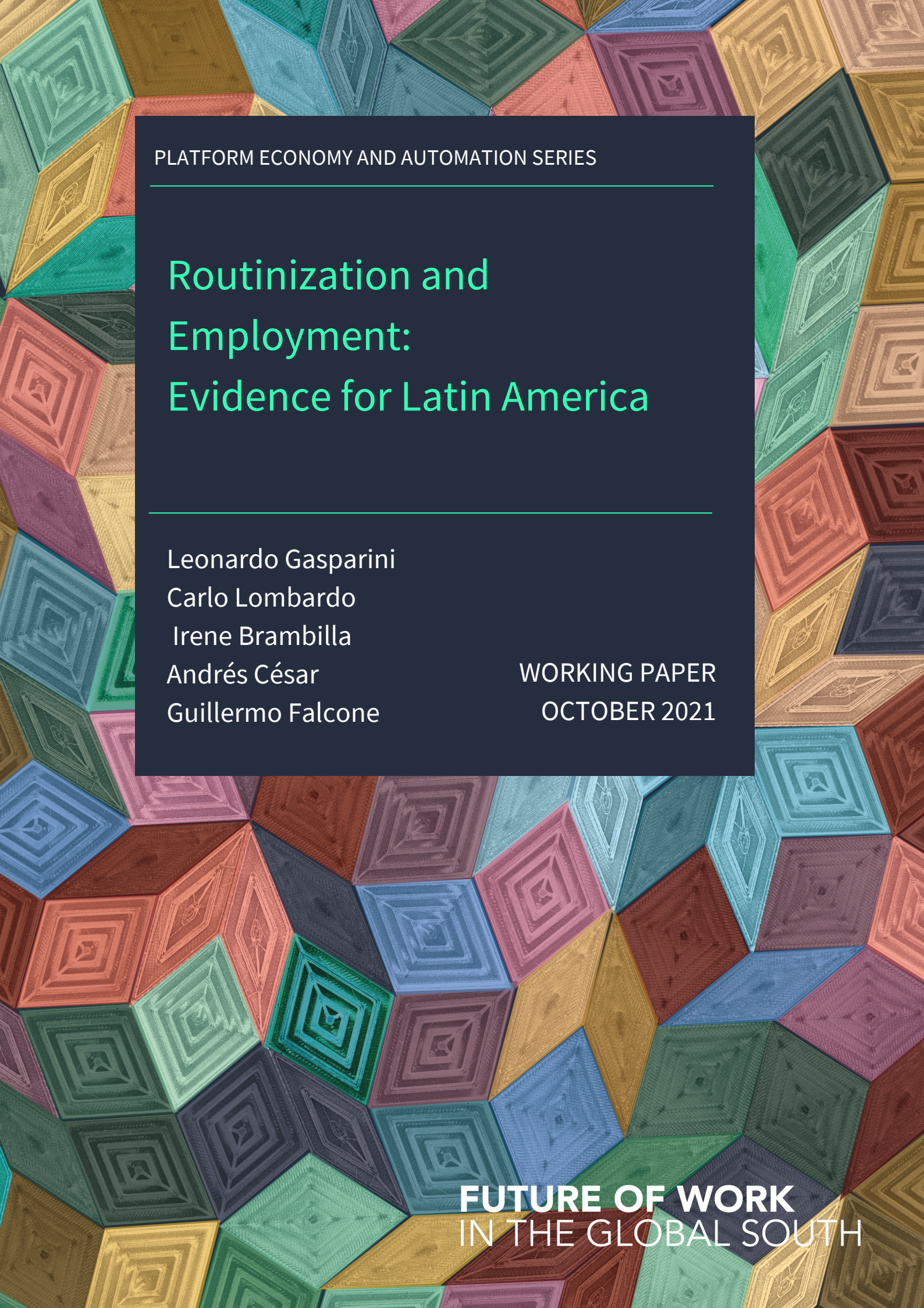

PLATFORM ECONOMY AND AUTOMATION SERIES

Routinization and Employment: Evidence for Latin America

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FUTURE OF WORK
IN THE GLOBAL SOUTH

Routinization and Employment:

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Abstract

We study changes in employment by occupations characterized by different degree of exposure to routinization in the six largest Latin American economies over the last two decades. We combine our own indicators of routine task content based on information from the Programme for the International Assessment of Adult Competencies (PIACC) with labor market microdata from harmonized national household surveys. We find that the increase in jobs 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.

Keywords: jobs, employment, technology, 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. Over the last decades a new concern has arisen: recent advances in digital technology and robotics are likely to replace labor routine tasks that follow well-defined rules, easily automated based on rule-based algorithms. This concern has been examined by the task-based approach of Autor *et al*. (2003) and Acemoglu and Autor (2011) who argue that the complementarity or substitutability between technology and labor does not occur at the worker category level but rather depends on how susceptible different tasks are for automation. Most papers for developed countries have found evidence in favor of the hypothesis of *job polarization*: labor routine tasks are heavily concentrated in the middle of the skills distribution, and hence employment has been increasingly concentrated in high-wage occupations and low-wage occupations, at the expense of traditionally middle-skill jobs.

In this paper we explore these issues by documenting the patterns of changes in employment by occupations characterized by different degree of exposure to routinization in the six largest Latin American economies (Argentina, Brazil, Chile, Colombia, Mexico and Peru, that represent 79% of total population and 86% of total GDP) over the last two decades. We combine (i) our own indicators of the degree of routinization based on information of task content by occupation from the Programme for the International Assessment of Adult Competencies survey (PIACC) with (ii) labor market microdata from harmonized national household surveys. In sum, we exploit a novel and rich dataset to construct measures of routine task content on the actual jobs of workers in Latin America and combine them with microdata from about 5 million workers in the six largest economies of the region over two decades.

We find that the exposure to routinization is heterogeneous across demographic and socioeconomic groups and across countries. The most salient asymmetry is among skill groups. The degree of routinization is higher among occupations of low-skill, low-relative wages. On average for the six largest

Latin American economies our index of routine task content (RTC) is 0.603 for the unskilled, somewhat smaller for the semi-skilled (0.527), and much lower for the skilled workers (0.341).

Changes in employment have been decreasing in the degree of routine task content of the occupations. This pattern was somewhat more marked during the expansionary 2000s than in the more sluggish 2010s. Although there is considerable heterogeneity across countries, the general result holds: in all six countries employment has increased less, or even decreased, in occupations with high routine task content. As a result of the asymmetric changes in employment, the overall degree of routinization has mildly decreased in the Latin American economies over the last two decades. The fall was more marked in the 2000s than in the 2010s. Between and within-sector changes are relevant to understand these patterns.

Our results are consistent with the literature that argues that workers that perform routine tasks are more likely to have been affected by automation. However, we do not find evidence for polarization in the labor market, as automatability is monotonically decreasing in wages. Growth in employment was increasing in the initial wage during the last two decades on average and in all countries. This asymmetric pattern was more intense in the 2000s.

In the period under analysis high-routine occupations experienced reductions in employment share but not in real and relative wages. In fact, the evidence suggests that when the economy was growing, unskilled low-wage workers in high-RTC occupations managed to get higher wage raises than the rest. Instead, in periods of stagnation there were little changes in the structure of relative wages.

We also explore the gender dimension of exposure to routinization and find that whereas on average women are not significantly different from men in their risks from automation, low-skill low-wage female workers performing tasks with high degree of routinization are particularly vulnerable.

The rest of this paper is organized as follows. In section 2 we review the literature on employment and routinization. In section 3 we provide details on the methodology applied and the data used. The main results are presented in section 4. In section 5 we extend the analysis by exploring results by gender

and in section 6 we include some robustness checks. The paper closes in section 7 with a discussion of the main results.

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 depends on how susceptible different tasks are for automation.[1] In particular, routine tasks that follow well-defined rules can be more easily automated based on rule-based algorithms, using increasingly powerful computers. 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 *et al.* 2006, 2008; Autor and Dorn, 2013; Goos and Manning, 2007; Goos *et al.* 2014; Michaels *et al.* 2013) and refers to the change in the structure of work in industrialized countries, with employment increasingly concentrated in high-education, high-wage occupations and low-education, low-wage occupations, at the expense of traditionally middle skill jobs.[2]

[1] Autor *et al.* (2003); Spitz-Oener (2006); Goos and Manning (2007); Goos *et al.* (2014) and Michaels *et al.* (2014).

[2] 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. More recently, Hunt and Nun (2019) assign US workers to real hourly wage bins with time-invariant thresholds and find a decline in the share of workers earning middle wages. However, they also

The literature on employment and automation in the developing world is still incipient, but growing.[3] Das and Hilgenstock (2018) propose a measure of the risk of displacement of labor by information technology based on Autor and Dorn (2013), and implement it for 85 countries. They find little evidence of polarization in developing countries. In part, this result is driven by the fact that developing economies are significantly less exposed to routinization than their developed counterparts. Maloney and Molina (2016) apply the Autor and Dorn (2016) approach to census data in 21 developing countries in Africa, Latin America and Asia. They do not find strong evidence for polarization in these LDCs. Changes in the occupational structure appear to be more in line with traditional skill-biased technological change mechanism. Messina *et al.* (2016) and Messina and Silva (2017) exploit the Skills Toward Employment and Productivity (STEP) Surveys conducted in Bolivia, Colombia, and El Salvador as a proxy for the routine/abstract/manual content of jobs in Latin America. They also find few signs of job polarization.

3. Data and methodology

In order to explore the correlations between employment changes and routinization we use two sources of information: the PIAAC survey to construct measures of routinization and a set of national household surveys to study labor market changes.

Measures of routinization

In this paper we use our own indexes of routine task content (RTC) constructed from microdata from the Programme for the International Assessment of Adult Competencies (PIAAC) surveys conducted by the OECD. In particular we take the mean results for the Latin American countries covered in the study: Chile, Ecuador, Mexico and Peru.[4] We focus on four specific job-related questions: Do you manage or supervise other people? Do you

show that the share of employment in low-wage occupations increased only for a short period (2002-2012).

[3] A regional study lead by the World Bank looks at several case studies of digital technology adoption in Latin America (Dutz et al. 2018).

[4] The results are highly correlated across countries.

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. Importantly, they have high variability in responses across individuals. For each individual in the survey we define a dummy variable for flexibility $F1$, which is equal to one when the individual replies that he or she performs at least one of the four tasks often or very often.

For each individual in the PIAAC survey we also know their occupation according to the ISCO 08 classification. We then use this information to define a routinization task content index RTC1 at the occupational level as the percentage of individuals in the occupation that do not perform any of the four activities above often. The index captures the percentage of individuals within an occupation that mostly perform routine tasks. The highest the RTC of an occupation, the higher the possibilities of automation. For robustness we define three additional flexibility indexes. Flexibility index $F2$ is a 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 $F3$ and $F4$ take values between 0 and 1 and capture the percentage of flexible tasks that the individual performs. For $F3$ we consider the first four questions, and for $F4$ we consider the longer list of six flexible tasks. Based on these flexibility indexes we construct alternative measures of RTC at the occupational level (RTC2, RTC3 and RTC4).

Table 3.1 shows the values of the different RTC indexes for the occupations at the ISCO 08 2-digit level. The correlations across indexes are high: all above 0.89. In what follows we focus on the RTC1 measure, but the main results are robust to the use of alternative indexes (see section 6). There are large heterogeneities in the routine task content across occupations (Figure 3.1). The index is lowest for managers and professionals and highest for some unskilled occupations, such as cleaners, agricultural laborers and refuse workers. The range of variation is large. From 0.091 for production and specialized services managers to 0.780 for cleaners and helpers. The average is 0.422 and the median 0.398.

A similar approach to the one described above is implemented in Autor, Levy, and Murnane (2003) and Autor, Katz, and Kearney (2006, 2008). For our purposes, our measure has an obvious advantage: it is constructed from information on actual tasks performed by Latin American workers. In the robustness section we compare our indicators with other measures that are based on information from the US and other developed countries. Some of these measures (e.g. Arntz *et al*., 2016; Frey and Osborne, 2017) capture the degree of potential automatability in the future and not the current level of routinization, which is more suitable for the purposes of this paper. In any case, the degree of correlation between these measures of actual routinization and potential automatability is very high (see section 6).

Labor market variables

In order to explore the labor market implications 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 (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 and over time by using similar definitions of variables in each country/year, and by applying consistent methods of processing the data (SEDLAC, 2020).

We focus on the period 2004-2019 and consider three time windows: the mid-2000s, the early 2010s and the late 2010s. In order to gain power we combine information for different years in each window. The first window includes years around 2005, the second one around 2011 and the third one around 2017. For simplicity we sometimes refer to these windows as simply

2005, 2011 and 2017. For example, in Argentina the mid-2000s includes surveys for 2004, 2005 and 2006, the early 2010s includes 2010, 2011 and 2012 and the late 2010s includes 2016, 2017 and 2018. Table 3.2 provides details on the information used in each country.

Nominal variables (hourly wages and monthly labor incomes) are deflated by the national CPIs of each country in order to make them comparable over time.[5] 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 converted the occupation codes of each country to the two-digit ISCO 08 classification using official crosswalks. Table 3.3 provides more information on this harmonization process.

Linking employment and routinization

The methodology we follow in the paper is straightforward. We look at medium-run changes in employment by occupations characterized by different degree of routinization. Specifically, we regress non-parametrically (lowess regressions) and parametrically (OLS and FE) the change in employment on (i) the routinization index of the occupation and (ii) the initial average wage of the occupation. The objective of the first set of regressions (the ones that use the routinization index) is to assess the hypothesis that routine tasks have been more affected in terms of employment. The objective of the second set of regressions (the ones that use the initial average wage) is to establish whether there is job polarization as in developed countries. We also look at potential gender biases of automation by comparing the degree of routinization of male vs. female jobs, and by applying estimations separately by gender.

4. Results

We start with a simple characterization of the working population in Latin America in terms of the degree of routinization of their occupations. The mean

[5] In Argentina, during the period 2007-2015 the national statistical office was intervened and the CPI lost credibility. For this period we use private estimates for inflation (see Gasparini *et al*. 2019).

value for the RTC1 index constructed from PIACC in the six largest Latin American economies for the late 2010s was 0.505. There is a great deal of heterogeneity in the degree of routinization across countries: from 0.471 in Argentina to 0.554 in Peru (Figure 4.1). It should be recalled that since RTC at the task level is fixed (due to data limitations), differences in the RTC levels across countries capture different national occupational structures. In that sense, Argentina, Chile and Brazil have occupational structures that imply RTC values below the regional mean, whereas Colombia, Mexico and Peru have employment structures more biased toward higher routinization occupations. The results are robust to the use of alternative RTC indexes (Table 4.1).

The heterogeneity in the degree of routinization across occupations translates into large differences in RTC across economic sectors, given that industries differ in their occupational structure. Table 4.2 shows the mean values (across the six Latin American economies) of the four routine-task content indexes defined from PIACC for the 17 sectors at the 1-digit ISIC. Construction, Transportation, Restaurants & Hotels, Domestic Services and Agriculture are the sectors with the highest degrees of routinization. In the other extreme, Finance, Teaching and Health & Social Services are those where automatization is less viable.

The degree of routinization also differs by socioeconomic and demographic characteristics of workers (Table 4.3). The RTC indexes are substantially lower among skilled workers. For instance, on average for the six economies the RTC1 is 0.603 for the unskilled, somewhat smaller for the semi-skilled (0.527), and much lower for the skilled workers (0.341).[6] Figure 4.2 shows the pattern for the complete range of years of education. The index of routine task content decreases very slowly up to around 10 years of education (corresponding to complete first level of secondary school) and more abruptly thereafter. The indexes are always larger for women than for men, although the differences are non-significant for skilled workers (Figure 4.3). We elaborate more on this in the next section. Differences in the degree of routinization by age are not as large as by skill (Figure 4.4). In any case, routinization seems to be high among very young workers. The RTC index decreases with age up to around age 28 and then slowly increases. Mean RTC goes from 0.580 for workers aged 18 to

[6] Semi-skilled are those with 9 to 13 years of education. The other two groups are defined accordingly.

0.479 for those aged 28, and then to 0.533 for workers in their mid-70s. There is however some heterogeneity in this pattern: RTC is actually mostly decreasing in age in Argentina.

Finally, there are some significant differences across the regions in which the territories of Latin American countries are usually divided (Table 4.4 and a map of RTC by region in Figure 4.5). In all countries the degree of routinization is somewhat higher in the poorest regions: NOA and NEA in Argentina; Norte and Nordeste in Brazil; Maule, Araucanía and Coquimbo in Chile; Pacífica and Atlántica in Colombia; Sur in Mexico and the rural areas and Selva in Peru.

Changes in employment

The Latin American economies experienced significant changes over the two decades under analysis. In particular, in South America economic growth was robust in the 2000s and weaker or inexistent in the 2010s. Per capita GDP grew at annual 3.6% in Colombia in the second half of the 2000s, and slowed down to 2.1% in the 2010s. In Chile the deceleration was from 3.6% to 1.6% and in Peru from 5.6% to 2.9%. The contrast was starker for Argentina and Brazil: they suffer recessions in the 2010s (the growth rates in both decades were 3.9% and -0.7% in Argentina, and 3% and -1% in Brazil). Mexico is the only country in our sample with a different pattern: per capita GDP grew at 0.4% in the mid-2000s and mildly speeded up to 1.4% in the 2010s.

Changes in employment are partly linked to GDP trends but they also have their own determinants and dynamics. In most countries the contrast between the two decades is noticeable for the employment rate (Figure 4.6 and Table 4.5). In Argentina and Peru the employment rate increased in the first period (2005-2011) and fell thereafter (2011-2017); Colombia experienced a deceleration, and Brazil a more intense fall in employment in the 2010s. Chile and Mexico are the two countries with a better employment performance in the 2010s. Against this backdrop, in what follows we analyze changes in the employment structure related to the degree of routinization.

Changes in employment and routinization

In this section we explore whether changes in employment in Latin America have been related to the degree of routinization of the different occupations. We start by exploring this relationship by means of simple non-parametric estimations (lowess regressions) at the occupation level. We consider three measures of employment: number of workers, number of full time workers and total hours of work. In all cases we assign workers to their main jobs, in case they have more than one.

Figure 4.7 shows the relationship between the annual rate of change in total number of workers and the degree of routinization by occupation. The figure includes observations from all six countries in our sample for the whole period, and then divided by decade. Changes in employment have been decreasing in the degree of routine task content of the occupations. In the more expansionary 2000s employment increased for all occupations, but especially for those with lower degree of routinization. In fact, the increase in jobs was negligible for occupations with high RTC. The pattern was similar although somewhat less marked during the more sluggish 2010s.[7] Although there is considerable heterogeneity across countries, the general result holds: in all six countries employment has increased less, or even decreased, in occupations with high routine task content (Figure A.8). The results are similar when considering full-time workers (Figure 4.9) and total hours of work (Figure 4.10).

In Figure 4.11 occupations are sorted in the horizontal axis by quintiles of the degree of routinization estimated by RTC1. In both periods the change in employment is decreasing in the RTC quintiles. In the 2000s gains in jobs were generalized but less significant among those occupations with high RTC. Whereas the number of workers in occupations with the lowest risk of automation (bottom quintile of RTC) grew 30% in the 2000s, the increase was much more modest in high routine task occupations: 7%. In the 2010s this asymmetric pattern was similar, although with lower changes in employment. In fact, the number of workers in occupations in the top RTC quintile went down by -0.2%.

[7] The pattern is not monotonically decreasing. There seems to be a very short range in which the employment growth rate was increasing in RTC in the 2010s.

We run some simple OLS and fixed-effects regression models to summarize these results. Formally,

$$g_{ict} = \alpha + \beta_1 . RTC_i . D_{1t} + \beta_2 . RTC_i . D_{2t} + \vartheta_c + \varepsilon_{ic}$$

where g_{ict} is the growth rate in jobs (alternatively, the growth in full-time jobs and in hours of work) in occupation i and country c during period t, RTC_i is our measure of routine task content of occupation i, and D labels the dummy for the period: D_{1t}=1 refers to the 2000s (the window 2005-2011) and D_{2t}=1 to the 2010s (2011-2017). The results of the estimations, shown in Table 4.6, are in line with the discussion above. Changes in jobs were decreasing in the routine task content of the occupation. The relationship is stronger (and more statistically significant) in the 2000s as compared to the 2010s.

As a result of the assymetric changes in employment, the overall degree of routinization has decreased in the Latin American economies over the last two decades (Figure 4.12). The fall was more marked in the 2000s than in the 2010s: the RTC1 fell from 0.518 to 0.510 between 2005 and 2011 and then to 0.505 in 2017. The other RTC indexes reveal a similar pattern of slow reduction in the degree of routinization over the last two decades (Table 4.7). It should be recalled that since we have just one observation of RTC in the period, the fall in the overall national index of RTC is just the consequence of changes in the employment structure toward occupations with lower degree of routinization. Mexico is the only country that experienced a different pattern: the increase in routinization, only noticeable in the 2000s, could have been mainly the consequence of outsourcing by US firms of more routine tasks.

Changes within and between sectors

In order to characterize changes in the structure of employment we follow Goos *et al*. (2014) and implement a between-within sector decomposition of the changes in employment shares by types of occupations in terms of the degree of routinization. With that aim we first divide occupations in terciles according to the value of RTC: low, mid and high RTC1. At any point in time workers are characterized by the RTC group and by the sector or industry (1-digit ISIC) of their main jobs. We decompose the overall change in employment shares for each RTC group into a within-industry and between-industry component. Formally,

$$\Delta\left(\frac{N_i}{N}\right) = \sum_s \frac{N_{ist}}{N_{st}} \Delta\left(\frac{N_s}{N}\right) + \sum_s \frac{N_{st'}}{N_{t'}} \Delta\left(\frac{N_{is}}{N_s}\right)$$

where N_{ist} labels employment in group of RTC i, sector or industry s and time period t. The change in the share of group i in total employment can be written as the sum of two terms: the between-sector component and the within-sector component. The first one records the change in i's employment share associated to changes in the sectoral structure of the economy while the second one records the direct impact of changes in the intensity of use of different occupations within sectors. Table 4.8 shows the results for each country of the decompositions measuring employment alternatively with number of workers (panel A) and hours of work (panel B).

Results are substantially heterogeneous across countries and over time. However, there are some common patterns, in particular a generalized fall in the participation of the high RTC group in all countries and periods (with the exception of Mexico). Consistently with the results in Goos *et al*. (2014) we find that within-industry and between-industry components are both quantitatively too large to be ignored in the analysis. The between effect is larger on average in both periods. It is also the larger effect in 7 out of the 11 country/period combinations in which the share of the high RTC went down. In sum, the results of the decompositions suggest that changes in the sectoral structure of the economy are very relevant to understand the pattern against employment in high routine occupations in Latin America.

Routinization and initial wages

In the last decades there has been a very active line of research that explores changes in the structure of jobs by skills. The typical analysis implies assessing changes in employment by occupations classified by initial wages, as rough measures of skills. In this section we explore that relationship with our data for Latin America. In Figure 4.13 we first plot our preferred RTC measure of routinization by occupation on the mean log hourly wage in the initial period (around 2005). The relationship is clearly decreasing in all countries: high-wage jobs are those with lower routine task content. The mean correlation coefficient for our sample of six countries is -0.831. The correlation coefficients

are also very high when computed with the median instead of the mean, and restricting the sample to full-time workers (Table 4.9).

Given the close negative relationship between routinization and initial wage, the results in Figure 4.14 are not surprising. Growth in employment was increasing in the initial wage during the last two decades on average and in all countries. A regression analysis (Table 4.10) confirms that the asymmetric pattern was more intense in the 2000s. In Figure 4.15 occupations are sorted by quintiles of the degree of routinization estimated by RTC1. In both periods the change in employment is increasing in the initial wage quintiles. Whereas the number of workers in occupations with high wages (top quintile) grew 28% in the 2000s, employment was virtually constant in low wage occupations. In the 2010s this asymmetric pattern was similar, although less marked.

These patterns provide no support for the polarization hypothesis that has been discussed for industrialized countries, according to which employment is increasingly concentrated in high-wage occupations and low-wage occupations, at the expense of traditionally middle-wage jobs. The evidence goes in line with other studies that find little evidence of polarization in developing countries (Das and Hilgenstock, 2018; Maloney and Molina, 2016; Messina and Silva, 2017).

Changes in wages

In this section we explore changes in wages across occupations characterized by different degrees of routinization. In Figure 4.16 we plot changes in the mean log wage for full time workers and the degree of routinization of their occupations. In general, there were gains in real wages over the period under analysis. Interestingly, gains were larger among those occupations with *higher* degree of routinization and *lower* initial wage.

The pattern of wage changes increasing in RTC is particularly clear in periods of economic expansion when wages increase in real terms. Instead, the pattern becomes substantially weaker in periods where real wages are sluggish. Figure 4.17 plots in the vertical axis the coefficients of country regressions of real median wage changes on RTC in the 2000s and 2010s and in the horizontal axis the annual change in real wages in those country/periods. There is a clear positive relationship between both variables. The coefficient of

a regression is 4.1 and statistically significant. The results are robust to other indexes of routinization, to the use of mean wages instead of median wages, and to the expansion of the analysis to full-time workers. In sum, the evidence suggests that when the economy was growing and real wages were increasing, unskilled low-wage workers in high-RTC occupations managed to get higher wage raises than the rest. Instead, in periods of stagnation there were little changes in the structure of relative wages.

5. Gender

In this section we explore whether there are heterogeneities across genders in terms of routinization and changes in employment. Table 5.1 reveals that the correlation between our measure of routine task content from PIACC and the share of female workers by occupation (index of "feminization") is positive but small (in fact in some countries it is not statistically significant). The relationship becomes stronger and statistically significant when ignoring women with high education (14 or more years). Consistent with this finding, Table 5.2 shows that in most countries (although not in all) the gender difference in terms of routinization of occupations is small in the high-education group and becomes larger for the rest. For instance, in Argentina whereas the mean value of the RTC index is 6% larger for female workers in the high-education group, it becomes 19% larger in the low-education group. This pattern holds in most countries in our sample, although with narrower gaps.

Figure 5.1 adds the gender dimension to the plot of changes in employment and the RTC index that we discussed in the previous section. Two facts are worth highlighting. First, on average employment grew substantially faster for women than for men, which is consistent with the long-run trend toward higher participation of women in the labor market. Second, for RTC values above the median, the negative gradient of the pattern employment change-RTC is much more marked for women than for men. In fact, while female employment grew substantially more than male employment in those occupations with low RTC, the gap vanished or even reversed in those with high RTC. Latin-American women with the skills needed for jobs with a low level of automatability benefited with large gains in employment and hours of

work, both in comparison with men and in absolute terms. In contrast, those in jobs easier to be performed by machines experienced stagnation or even fall in employment and hours of work, a pattern similar (or possibly worse)[8] than their male counterparts. The group of low-skill low-wage female workers performing tasks with high degree of routinization seems to be particularly vulnerable to the process of automation.

6. Robustness

Our results are robust to the use of alternative indexes of routine task content constructed from PIACC. Figure 6.1 shows the relationship between employment change and routinization for indexes RTC2, RTC3 and RTC4 discussed in section 3. In all cases the main results hold: employment changes were decreasing in the routine task content over the period under analysis (see also Table 6.1).

Probably the most popular measure of routineness of an occupation is the Routine Task Intensity (RTI) index used by Autor and Dorn (2013) and Autor, Dorn, and Hanson (2013) and based on the US Dictionary of Occupational Titles. The RTI measure is based on three task measures: Manual, Routine and Abstract task measures. From these three measures the RTI index is constructed as the difference between the log of Routine tasks and the sum of the log of Abstract and the log of Manual tasks. The correlation between the measure used by Autor and Dorn and our RTC indexes based on PIACC are very high. For instance the linear correlation coefficient with RTC1 is 0.84. Consequently, our results do not substantially change when using the Autor and Dorn measure of RTI (Figure 6.2 and Table 6.1).

Our indexes constructed from PIACC use information of the actual tasks currently performed by Latin American workers. 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? There have been a number of initiatives to estimate the capability of substituting occupations with machines in the near future. So far, the most

[8] The curve for women in Figure 5.1 in the 2010s crosses the curve for men, although it does so for very high RTC values, where estimations are more imprecise.

popular approach follows the study of Frey and Osborne (2017) (FO). 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).[9] 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. 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 the predictions of this model as indicator of true automatability.

The FO index and the variation proposed by Arntz *et al*. (2017) are conceptually different from our indexes for routine task content. Those are indexes of future automatability that measure the risk for routinization in some developed economies in the near future, while ours are indexes of the current degree of routinization faced by Latin American workers. However, the correlation between all these measures is high. For instance, the linear correlation coefficient between our RTC1 and the FO (Arntz) index is 0.78 (0.72). Predictably, the main results of our paper do not substantially change if we consider these two indexes of risk of automation (Figure 6.3). Table 6.1 reveals that, as expected, this relationship is somewhat looser than when considering the degree of current routinization for Latin American workers (our RTC).

7. Concluding remarks

In this paper we study changes in employment by occupations characterized by different degree of exposure to routinization in the six largest Latin American economies over the last two decades. To that aim we use our own measures of degree of routinization by occupation constructed from the answers of Latin American workers to the Programme for the International

[9] 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).

Assessment of Adult Competencies survey. In this concluding section we stress six points.

1. Given different occupational structures, the exposure to routinization is heterogeneous across demographic and socioeconomic groups and across countries. The most salient asymmetry is among skill groups: our index of routine task content decreases very slowly up to around 10 years of education and fell abruptly thereafter. This pattern is key to understand some of our findings.

2. Our results are consistent with the literature that argues that workers that perform routine tasks are more likely to have been affected by automation. Over the period under study the increase in jobs was significantly decreasing in the degree of routinization. At least since the mid-2000s the labor structure in Latin America has moved slowly toward occupations with a lower degree of exposure to routinization.

3. The magnitude of the changes have not been uniform over time. During the expansionary 2000s employment increased for every group, but especially in those occupations less affected by the ongoing process of increasing automation. The pattern was similar although less marked during the more sluggish 2010s.

4. Given the decreasing pattern of RTC in education, and in line with most of the previous literature in LDCs, we do not find evidence for polarization in the labor market. Maloney and Molina (2016) suggest some possible reasons why in contrast to advanced economies polarization does not show up (at least so far) in developing countries data. Different initial occupational distributions, impact of off-shored jobs or the effect of new technologies in fostering sectors that employ middle-skill jobs could be some possible explanations. More research is needed to understand these factors.

5. In the period under analysis high-routine occupations experienced reductions in employment share but not in real and relative wages. In fact, the evidence suggests that when the economy was growing, unskilled low-wage workers in high-RTC occupations managed to get higher wage raises than the rest. Instead, in periods of stagnation there were little changes in the structure of relative wages.

6. There might be a gender dimension in this issue. We find that the gender difference in terms of routinization of occupations is significant, except in the high-education group. Moreover, we find gender differences in employment changes over time. In particular, whereas female employment grew substantially more than male employment in jobs with low level of automatability, the gap vanished or even reversed among high routine task content jobs. The group of low-skill low-wage female workers performing tasks with high degree of routinization seems to be particularly vulnerable to the process of automation.

References

Acemoglu, D., and D. Autor (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of labor economics* (Vol. 4, pp. 1043-1171). Elsevier.

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

Autor, D. , L. Katz, and M.Kearney (2006). The Polarization of the U.S. Labor Market. American Economic Review Papers and Proceedings 96 (2), 189-194.

Autor, D. L. Katz, and M. Kearney (2008). Trends in U.S. Wage Inequality: Revising the Revisionists. Review of Economics and Statistics 90 (2), 300-323.

Autor, D. H. (2013). The Task Approach to Labor Markets: An Overview. Journal for Labour Market Research 46 (3), 185-199.

Autor, David H., and David Dorn. (2013). "The Growth of Low-Skill Service Jobs and the Polarization of the US Labour Market." *American Economic Review*, Vol. 103, No. 5, August, pp. 1553-97.

Autor, D. H., and M. J. Handel (2013). Putting tasks to the test: Human capital, job tasks, and wages. *Journal of labor Economics*, *31*(S1), S59-S96.

Bosch, M., Pages, C. and Ripani, L. (2018). El futuro del trabajo en América Latina y el Caribe. BID.

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

Card, D. and T. Lemieux (2001). Can falling supply explain the rising return to college for younger men? A cohort-based analysis. *The Quarterly Journal of Economics*, *116*(2), 705-746.

Goos, M. and A. Manning (2007). Lousy and Lovely jobs: The Rising Polarization of Work in Britain. Review of Economics and Statistics 89 (1), 118-133.

Goos, M., A. Manning, and A. Salomons (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, *104*(8), 2509-26.

Katz, L. F., and K. M. Murphy (1992). Changes in relative wages, 1963–1987: supply and demand factors. *The quarterly journal of economics*, *107*(1), 35-78.

Maloney, W. and Molina, C. (2016). Are Automation and Trade Polarizing Developing Country Labor Markets, Too? World Bank Policy Research Working paper 7922

Messina, J., G. Pica, and A. Oviedo (2016). "Job Polarization in Latin America." Inter-American Development Bank, Washington, DC. Unpublished. Available at: http://www.jsmessina.com.

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

Michaels, G., A. Natraj, J. Van Reenen, and J. Reenen (2013). Has ICT Polarized Skill Demand? Evidence from Eleven Countries over 25 Years. Review of Economics and Statistics 96 (1), 60-77.

Santos, I, Monroy, S.and Moreno, M. (2015). Technological Change and Labor Market Disruptions: evidence from the developing world. Mimeo.

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

World Bank (2016) *World Development Report 2016: Digital Dividends*. Washington, DC: World Bank.

Table 3.1: Indices of routinization by occupation

	Indexes of Routinization			
Occupation	RTC1	RTC2	RTC3	RTC4
Chief Executives, Senior Officials and Legislators	0.189	0.101	0.589	0.517
Production and Specialized Services Managers	0.091	0.037	0.450	0.418
Hospitality, Retail and Other Services Managers	0.157	0.025	0.563	0.457
Science and Engineering Professionals	0.207	0.111	0.617	0.585
Health Professionals	0.244	0.084	0.657	0.602
Teaching Professionals	0.286	0.104	0.689	0.643
Business and Administration Professionals	0.200	0.073	0.625	0.539
Information and Communications Technology Professionals	0.184	0.108	0.614	0.603
Legal, Social and Cultural Professionals	0.254	0.090	0.677	0.634
Science and Engineering Associate Professionals	0.211	0.131	0.591	0.580
Health Associate Professionals	0.383	0.176	0.729	0.681
Business and Administration Associate Professionals	0.260	0.085	0.668	0.572
Legal, Social, Cultural and Related Associate Professionals	0.282	0.111	0.690	0.616
Information and Communications Technicians	0.290	0.141	0.654	0.617
General and Keyboard Clerks	0.475	0.262	0.799	0.732
Customer Services Clerks	0.400	0.129	0.764	0.654
Numerical and Material Recording Clerks	0.377	0.178	0.722	0.656
Other Clerical Support Workers	0.397	0.182	0.699	0.640
Personal Services Workers	0.582	0.258	0.840	0.739
Sales Workers	0.513	0.111	0.816	0.663
Personal Care Workers	0.379	0.237	0.760	0.734
Protective Services Workers	0.359	0.277	0.723	0.731
Market-oriented Skilled Agricultural Workers	0.659	0.468	0.886	0.845
Market-oriented Skilled Forestry, Fishery and Hunting Workers	0.542	0.293	0.856	0.811
Building and Related Trades Workers (excluding Electricians)	0.494	0.302	0.793	0.737
Metal, Machinery and Related Trades Workers	0.416	0.245	0.771	0.717
Handicraft and Printing Workers	0.466	0.277	0.779	0.726
Electrical and Electronic Trades Workers	0.363	0.234	0.730	0.701
Food Processing, Woodworking, Garment and Other Craft and Re	0.579	0.348	0.852	0.790
Stationary Plant and Machine Operators	0.520	0.387	0.825	0.813
Drivers and Mobile Plant Operators	0.583	0.338	0.863	0.809
Cleaners and Helpers	0.780	0.655	0.925	0.909
Agricultural, Forestry and Fishery Labourers	0.772	0.618	0.932	0.907
Labourers in Mining, Construction, Manufacturing and Transport	0.667	0.495	0.877	0.845
Food Preparation Assistants	0.696	0.339	0.899	0.809
Street and Related Sales and Services Workers	0.702	0.231	0.915	0.775
Refuse Workers and Other Elementary Workers	0.668	0.480	0.893	0.856

Source: own calculations based on PIACC.

Table 3.2: Information from national household surveys

country	survey	acronym	Mid 2000s	Early 2010s	Late 2010s
Argentina	Encuesta Permanente de Hogares	EPH	2004-2006	2010-2012	2016-2018
Brazil	Pesquisa Nacional por Amostra de Domicilios	PNAD	2004-2006	2011-2013	2017-2019
Chile	Encuesta de Caracterización Socioeconómica Nacional	CASEN	2003	2011	2017
Colombia	Gran Encuesta Integrada de Hogares	GEIH	2003-2005	2010-2012	2016-2018
Mexico	Encuesta Nacional de Ingresos y Gastos de los Hogares	ENIGH	2004 & 2006	2010 & 2012	2016 & 2018
Peru	Encuesta Nacional de Hogares	ENAHO	2004-2006	2010-2012	2016-2018

Source: own calculations based on national household surveys.

Table 3.3: Harmonization of occupation codes

Country	Time span analyzed	Original occupational classification	ISCO-08 harmonization process	Details
ARG	2004-2018	Clasificador Nacional de Ocupaciones - 2001	Official crosswalk provided by INDEC	Link to INDEC's crosswalk: https://www.indec.gob.ar/ftp/cuadros/menusuperior/eph/CONVERSION_CNO-01_CIUO-08.xls
BRA	2004-2013	Classificação Brasileira de Ocupações Domiciliar	Own ad-hoc crosswalk	-
	2017-2019	Classificação de Ocupações para Pesquisas Domiciliares		-
CHL	2003-2017	International Standard Classification of Occupations - 1988	Own ad-hoc crosswalk based on ILO official crosswalk	Link to ILO's crosswalk: http://www.ilo.org/public/english/bureau/stat/isco/docs/corrtab08-88.xls
COL	2003-2018	Clasifiación Nacional de Ocupaciones - 1970	Own ad-hoc crosswalk based on DANE crosswalk and individual's educational attainment	We thank DANE for sending us their crosswalk between CNO-70 and ISCO-08
MEX	2004-2006	Clasificación Mexicana de Ocupaciones	Own ad-hoc crosswalk	-
	2010	Clasificación Única de Ocupaciones	Own ad-hoc crosswalk	-
	2012-2018	Sistema Nacional de Clasificación de Ocupaciones	Own ad-hoc crosswalk	-
PER	2004-2018	Código de Ocupaciones 1995	Own ad-hoc crosswalk based on INEI crosswalk	Link to INEI's crosswalk: https://www.inei.gob.pe/media/Tablas_de_correspondencia_CNO_CIUO_CO.xlsx

Source: own elaboration based on national household surveys.

Table 4.1: RCT by country, late 2010s

	RCT1	RCT2	RCT3	RCT4
Argentina	0.471	0.260	0.778	0.714
Brazil	0.489	0.276	0.790	0.725
Chile	0.473	0.272	0.781	0.718
Colombia	0.518	0.278	0.807	0.737
Mexico	0.527	0.310	0.809	0.747
Peru	0.554	0.331	0.826	0.762
All	0.505	0.288	0.799	0.734

Source: own calculations based on national household surveys and PIACC.

Table 4.2: Indices of routinization by industry
Latin America

	Indexes of routinization			
Industry	RTC1	RTC2	RTC3	RTC4
Agriculture & forestry	0.683	0.508	0.890	0.854
Fishing	0.573	0.359	0.853	0.806
Mining & quarrying	0.461	0.298	0.769	0.730
Manufacturing	0.487	0.296	0.791	0.738
Utilities	0.414	0.251	0.740	0.694
Construction	0.503	0.326	0.793	0.745
Commerce	0.500	0.180	0.801	0.686
Restaurants & hotels	0.542	0.256	0.817	0.725
Transportation & communications	0.519	0.296	0.815	0.758
Finance	0.334	0.139	0.697	0.616
Business services	0.396	0.228	0.732	0.678
Public administration	0.389	0.222	0.732	0.682
Teaching	0.339	0.159	0.709	0.661
Health & social services	0.366	0.178	0.722	0.666
Other services	0.490	0.261	0.789	0.718
Domestic servants	0.646	0.470	0.871	0.837
Extra-territorial organizations	0.315	0.145	0.687	0.624

Source: own calculations based on national household surveys and PIACC.
Note: mean value across Argentina, Brazil, Chile, Colombia, Mexico and Peru.

Table 4.3: Indices of routinization by skill, gender and age Latin America

	Indexes of Routinization			
	RTC1	RTC2	RTC3	RTC4
Skill				
Unskilled	0.603	0.386	0.852	0.795
Semi-skilled	0.527	0.294	0.813	0.744
Skilled	0.341	0.153	0.702	0.638
Gender				
Women	0.507	0.274	0.799	0.727
Men	0.504	0.299	0.798	0.739
Age				
[15,24]	0.541	0.308	0.820	0.752
[25,40]	0.484	0.269	0.787	0.722
[41,64]	0.505	0.292	0.798	0.735
[65+]	0.530	0.307	0.811	0.744

Source: own calculations based on national household surveys and PIACC.
Note: mean value across Argentina, Brazil, Chile, Colombia, Mexico and Peru.

Table 4.4: Indices of routinization by region

Country	Region	RTC
Argentina	GBA	0.470
Argentina	Pampeana	0.469
Argentina	Cuyo	0.472
Argentina	NOA	0.479
Argentina	Patagonia	0.461
Argentina	NEA	0.475
Brasil	Norte	0.518
Brasil	Nordeste	0.517
Brasil	Sudeste	0.472
Brasil	Sur	0.483
Brasil	Centro-Oeste	0.491
Chile	Tarapacá	0.471
Chile	Antofagasta	0.444
Chile	Atacama	0.470
Chile	Coquimbo	0.516
Chile	Valparaíso	0.488
Chile	Libertador Gral. B. O'Higgins	0.533
Chile	Maule	0.538
Chile	Biobío	0.496
Chile	Araucanía	0.497
Chile	Los Lagos	0.488
Chile	Aysén del Gral. Carlos Ibáñez	0.458
Chile	Magallanes y de la Antártica	0.443
Chile	Region Metropolitana de Santiago	0.445

Country	Region	RTC
Colombia	Atlántica	0.523
Colombia	Oriental	0.532
Colombia	Central	0.525
Colombia	Pacífica	0.541
Colombia	Santa Fe de Bogotá	0.456
Mexico	Noroeste	0.508
Mexico	Norte	0.519
Mexico	Noreste	0.492
Mexico	Centro-Occidente	0.532
Mexico	Centro-Este	0.510
Mexico	Sur	0.587
Mexico	Oriente	0.566
Mexico	Peninsula de Yucatan	0.520
Peru	Costa Urbana	0.533
Peru	Sierra Urbana	0.530
Peru	Selva Urbana	0.547
Peru	Costa Rural	0.661
Peru	Sierra Rural	0.677
Peru	Selva Rural	0.679
Peru	Lima Metropolitana	0.477

Source: own calculations based on national household surveys and PIACC.

Table 4.5: Annual changes in employment rate

	2000s	2010s
Argentina	0.19	-0.32
Brazil	-0.18	-1.02
Chile	0.01	0.52
Colombia	0.47	0.19
Mexico	-0.05	0.56
Peru	0.63	-0.27

Source: own calculations based on national household surveys.

Table 4.6: Regressions of employment growth on RTC

	Number of workers					
	Diff. 2000s		Diff. 2010s		Diff. 2000s-2010s	
	(1)	(2)	(3)	(4)	(5)	(6)
RTC1	-0.286*	-0.306**	-0.260*	-0.246*	-0.507**	-0.512**
	(0.111)	(0.106)	(0.106)	(0.109)	(0.140)	(0.143)
Constant	0.248***	0.225***	0.167**	0.116*	0.407***	0.328***
	(0.0475)	(0.0461)	(0.0572)	(0.0475)	(0.0470)	(0.0626)
Obs.	182	182	182	182	182	182
R-squared	0.045	0.075	0.032	0.148	0.057	0.100
Country FE	NO	YES	NO	YES	NO	YES
	Number of full-time workers					
	Diff. 2000s		Diff. 2010s		Diff. 2000s-2010s	
	(7)	(8)	(9)	(10)	(11)	(12)
RTC1	-0.332***	-0.354***	-0.277**	-0.266**	-0.567***	-0.581***
	(0.0625)	(0.0628)	(0.0990)	(0.100)	(0.130)	(0.132)
Constant	0.293***	0.313***	0.166**	0.0693	0.452***	0.368***
	(0.0393)	(0.0274)	(0.0579)	(0.0437)	(0.0519)	(0.0578)
Obs.	182	182	182	182	182	182
R-squared	0.053	0.088	0.034	0.168	0.063	0.103
Country FE	NO	YES	NO	YES	NO	YES
	Hours worked					
	Diff. 2000s		Diff. 2010s		Diff. 2000s-2010s	
	(13)	(14)	(15)	(16)	(17)	(18)
RTC1	-0.292**	-0.317***	-0.274*	-0.264*	-0.519**	-0.534**
	(0.0807)	(0.0768)	(0.115)	(0.118)	(0.143)	(0.145)
Constant	0.252***	0.238***	0.152*	0.0627	0.391***	0.281***
	(0.0374)	(0.0335)	(0.0647)	(0.0513)	(0.0491)	(0.0633)
Obs.	182	182	182	182	182	182
R-squared	0.045	0.081	0.035	0.171	0.059	0.117
Country FE	NO	YES	NO	YES	NO	YES

Note: Robust standard errors clustered at the country level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4.7: Indicators of routine task content
Latin America

	RCT1	RCT2	RCT3	RCT4
Mid-2000s	0.518	0.301	0.804	0.741
Early 2010s	0.510	0.292	0.801	0.737
Late 2010s	0.505	0.288	0.799	0.734

Source: own calculations based on national household surveys and PIACC.
Note: mean values across Argentina, Brazil, Chile, Colombia, Mexico and Peru.

Table 4.8: Between and within decomposition of changes in employment shares

A. Number of workers

	2005-2011			2011-2017		
	Overall	Between	Within	Overall	Between	Within
Argentina						
Low RTC	1.5	0.1	1.4	-1.5	0.3	-1.8
Mid RTC	0.7	-0.4	1.1	2.1	0.2	1.9
High RTC	-2.2	0.3	-2.5	-0.6	-0.6	0.0
Brazil						
Low RTC	2.3	1.2	1.1	3.6	3.3	0.3
Mid RTC	5.4	3.7	1.7	4.3	1.0	3.3
High RTC	-7.7	-4.9	-2.8	-7.9	-4.3	-3.6
Chile						
Low RTC	-0.5	1.5	-2.0	1.4	1.1	0.3
Mid RTC	1.0	0.8	0.3	0.4	-0.7	1.2
High RTC	-0.6	-2.3	1.7	-1.8	-0.4	-1.4
Colombia						
Low RTC	-0.6	0.2	-0.8	1.1	0.8	0.3
Mid RTC	3.8	0.6	3.3	-1.0	0.1	-1.1
High RTC	-3.2	-0.8	-2.4	-0.1	-0.9	0.8
Mexico						
Low RTC	-2.0	0.8	-2.8	0.2	-0.1	0.2
Mid RTC	2.5	0.9	1.6	-1.3	-0.4	-0.9
High RTC	-0.5	-1.7	1.1	1.1	0.4	0.7
Peru						
Low RTC	3.2	2.3	0.9	0.7	0.1	0.6
Mid RTC	2.8	2.5	0.3	0.0	0.0	0.0
High RTC	-6.0	-4.8	-1.2	-0.8	-0.1	-0.6

Table 4.8 (cont.): Between and within decomposition of changes in employment shares

B. Hours of work

	2005-2011			2011-2017		
	Overall	Between	Within	Overall	Between	Within
Argentina						
Low RTC	1.2	0.3	0.9	-1.4	0.5	-1.9
Mid RTC	0.4	-0.6	1.0	2.3	0.4	1.9
High RTC	-1.6	0.3	-2.0	-0.9	-0.8	0.0
Brazil						
Low RTC	2.3	1.1	1.1	3.8	2.9	0.9
Mid RTC	5.3	3.5	1.8	3.4	0.2	3.2
High RTC	-7.5	-4.6	-2.9	-7.2	-3.1	-4.1
Chile						
Low RTC	0.2	1.9	-1.7	1.4	1.2	0.2
Mid RTC	0.9	0.7	0.2	0.5	-0.7	1.2
High RTC	-1.1	-2.6	1.5	-1.9	-0.5	-1.4
Colombia						
Low RTC	-0.5	0.3	-0.8	1.1	0.9	0.2
Mid RTC	3.4	0.5	2.8	-1.2	0.1	-1.4
High RTC	-2.8	-0.8	-2.0	0.1	-1.1	1.1
Mexico						
Low RTC	-2.5	0.8	-3.4	0.3	0.0	0.3
Mid RTC	2.6	1.3	1.3	-1.3	-0.4	-1.0
High RTC	0.0	-2.1	2.1	1.1	0.4	0.7
Peru						
Low RTC	3.4	2.3	1.1	0.6	0.2	0.5
Mid RTC	2.9	2.3	0.6	-0.4	0.1	-0.4
High RTC	-6.3	-4.6	-1.7	-0.3	-0.2	0.0

Source: own calculations based on national household surveys and PIACC.

Table 4.9: Linear correlation between RTC and initial wage

	(i)	(ii)	(iii)	(iv)
Argentina	-0.853	-0.840	-0.850	-0.832
Brazil	-0.817	-0.839	-0.814	-0.829
Chile	-0.818	-0.821	-0.811	-0.813
Colombia	-0.826	-0.829	-0.800	-0.798
Mexico	-0.846	-0.864	-0.841	-0.854
Peru	-0.827	-0.829	-0.832	-0.833
Mean	-0.831	-0.837	-0.825	-0.827

Source: own calculations based on national household surveys and PIACC.
Note: Correlations of RTC1 with (i) mean log wage,
(ii) mean log wage full-time workers, (iii) median log wage,
(iv) median log wage full-time workers.

Table 4.10: Regressions of employment growth on initial wage

	Number of workers			Number of full-time workers			Hours worked		
	2000s	2010s	All	2000s	2010s	All	2000s	2010s	All
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
log wages 2005	0.124**	0.0803*	0.197***	0.146***	0.0906**	0.232***	0.137***	0.0938*	0.221***
	(0.0368)	(0.0367)	(0.0354)	(0.0257)	(0.0347)	(0.0329)	(0.0315)	(0.0401)	(0.0407)
Constant	-0.0917	-0.110*	-0.186**	-0.0570	-0.181**	-0.228***	-0.103*	-0.191**	-0.278***
	(0.0543)	(0.0542)	(0.0523)	(0.0380)	(0.0512)	(0.0485)	(0.0465)	(0.0592)	(0.0601)
Observations	181	181	181	181	181	181	181	181	181
R-squared	0.096	0.143	0.118	0.122	0.170	0.136	0.114	0.174	0.152
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Source: own calculations based on national household surveys and PIACC.
Note: Robust standard errors clustered at the country level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5.1. Coefficients of correlation between RTC and share of female workers by occupation Latin America

	All	Low and mid education
2005	0.058	0.127
2011	0.059	0.152
2017	0.054	0.148

Source: own calculations based on national household surveys and PIACC.
Note: mean value across Argentina, Brazil, Chile, Colombia, Mexico and Peru.

Table 5.2. RTC index by gender and education

	Low	Middle	High	Total
Argentina				
Women	0.632	0.533	0.360	0.482
Men	0.532	0.485	0.339	0.461
Brazil				
Women	0.630	0.510	0.321	0.487
Men	0.556	0.482	0.301	0.477
Chile				
Women	0.629	0.523	0.328	0.467
Men	0.592	0.520	0.330	0.478
Colombia				
Women	0.583	0.542	0.346	0.512
Men	0.597	0.520	0.320	0.523
Mexico				
Women	0.620	0.545	0.336	0.521
Men	0.580	0.518	0.337	0.502
Peru				
Women	0.640	0.571	0.390	0.560
Men	0.642	0.569	0.373	0.549

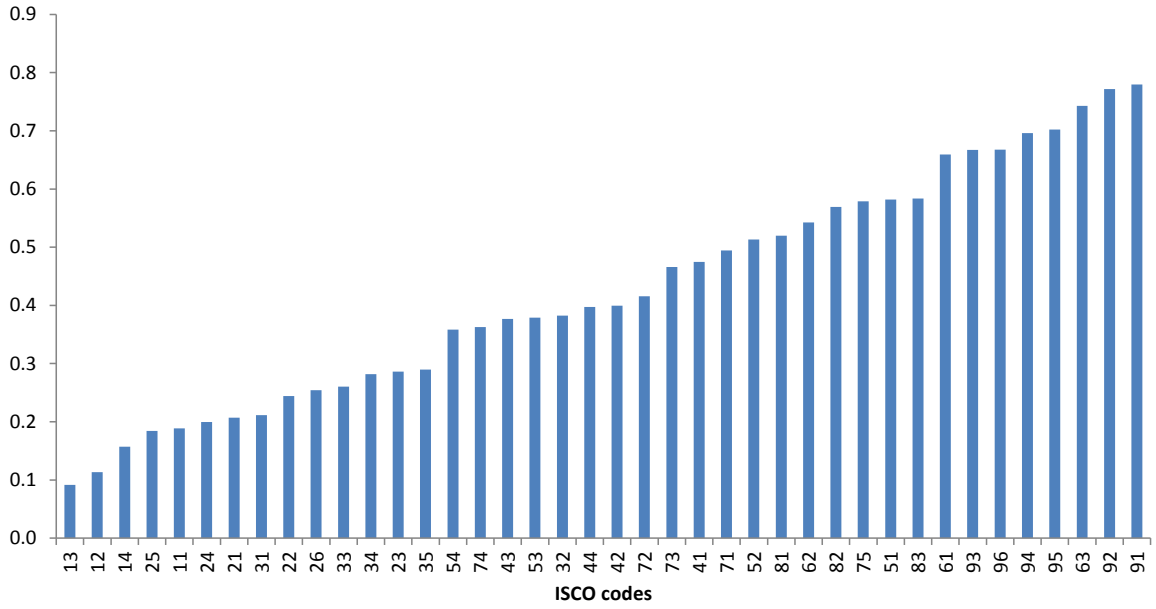
Source: own calculations based on national household surveys and PIACC.

Table 6.1: Robustness analysis. Regressions of employment growth

	RTC1	RTC2	RTC3	RTC4	Autor & Dorn	Frey & Osborne	Arntz *et al.*
	(1)	(2)	(3)	(4)	(10)	(12)	(14)
Dep. var: Growth rate in number of workers (2005-2017)	-0.512**	-0.570*	-0.783**	-0.759**	-0.527**	-0.477***	-0.427*
	(0.143)	(0.224)	(0.203)	(0.233)	(0.191)	(0.0866)	(0.203)
Constant	0.328***	0.248***	0.698***	0.638**	0.360**	0.370***	0.160***
	(0.0626)	(0.0561)	(0.153)	(0.164)	(0.0925)	(0.0480)	(0.0263)
Obs.	182	182	182	182	182	182	182
R-squared	0.100	0.095	0.093	0.093	0.093	0.150	0.058
Country FE	YES	YES	YES	YES	YES	YES	YES

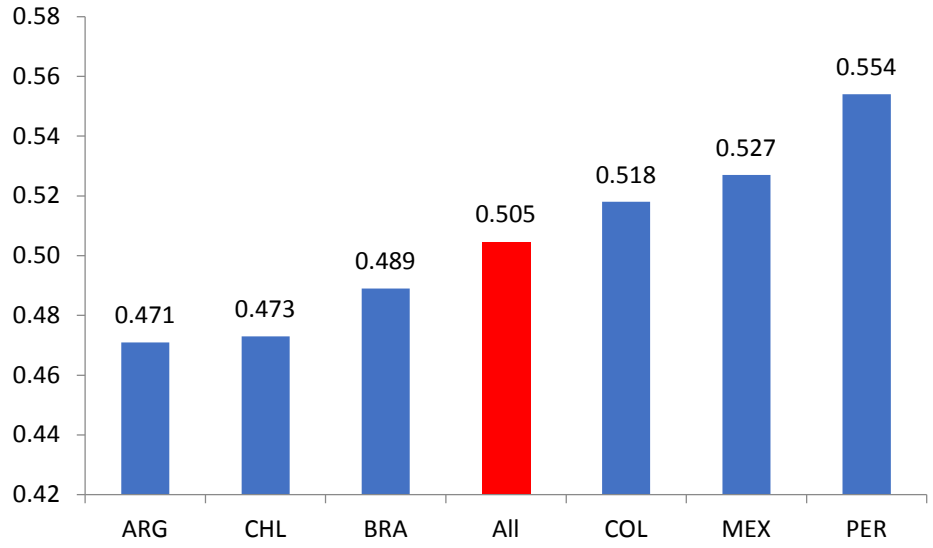
Notes. Columns represent different independent variables of interest. The dependent variable of each regression is the growth rate in the number of workers between 2005 and 2017.
Robust standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Figure 3.1: Indices of routinization by occupation



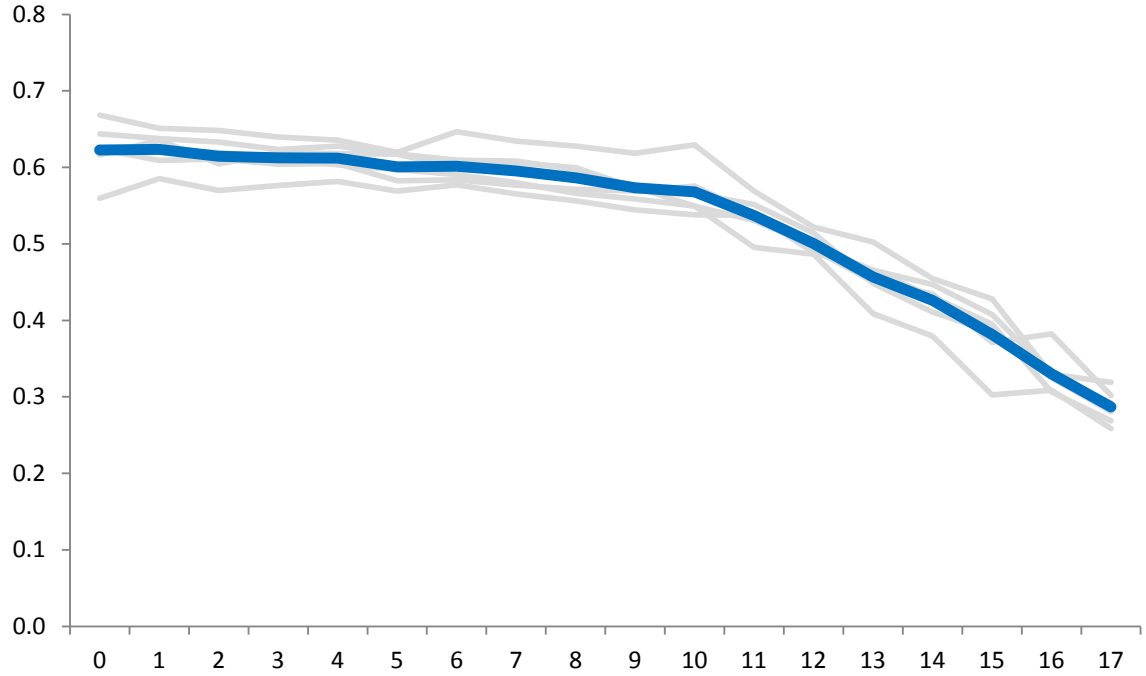
Source: own calculations based on PIACC.

Figure 4.1: Indices of routinization by country



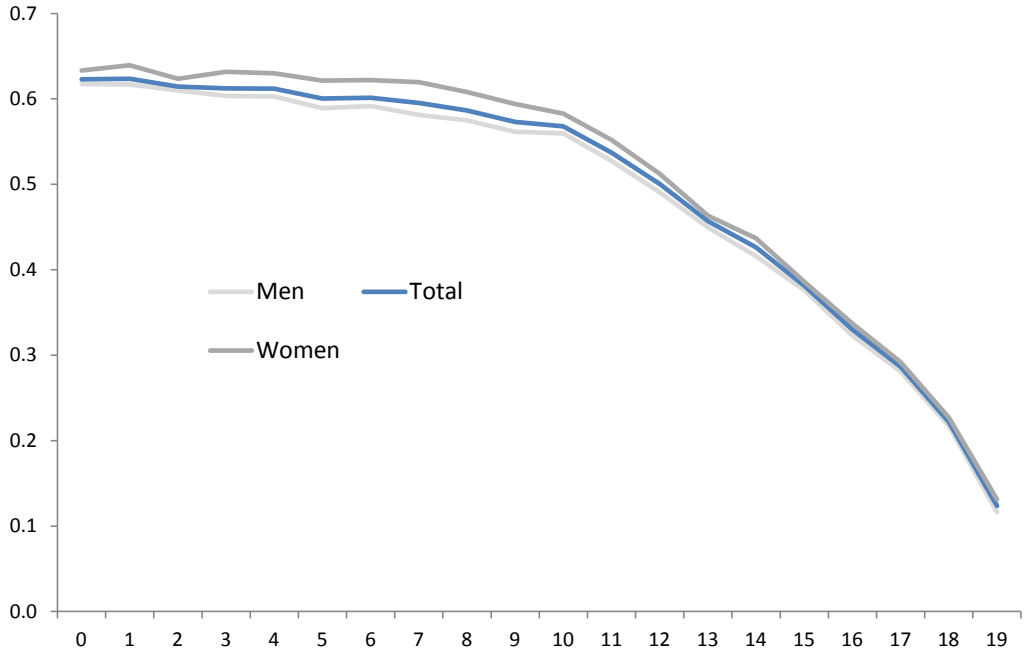
Source: own calculations based on PIACC and national household surveys of late 2010s.

Figure 4.2: Indices of routinization by years of education
Latin America



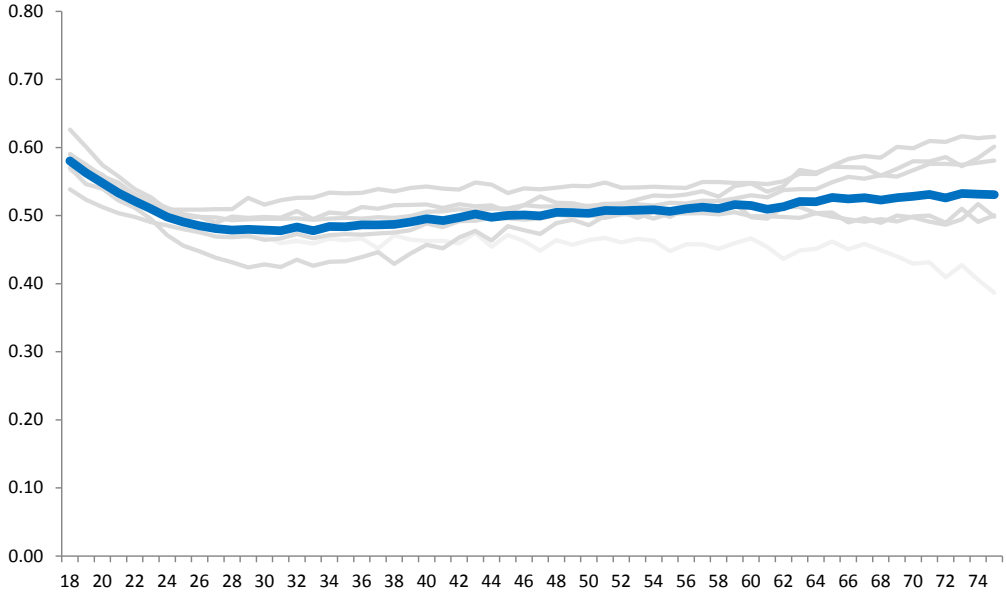
Source: own calculations based on PIACC and national household surveys of late 2010s.
Note: each grey line shows a different country.

Figure 4.3: Indices of routinization by years of education and gender
Latin America



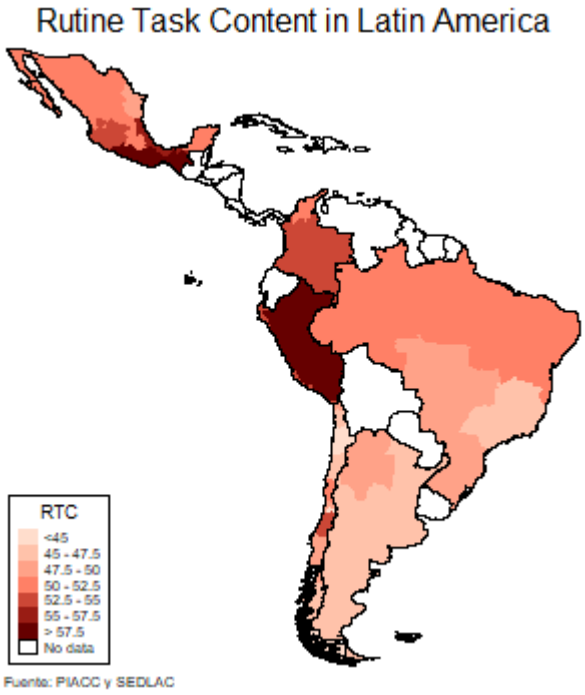
Source: own calculations based on PIACC and national household surveys of late 2010s.

Figure 4.4: Indices of routinization by age
Latin America



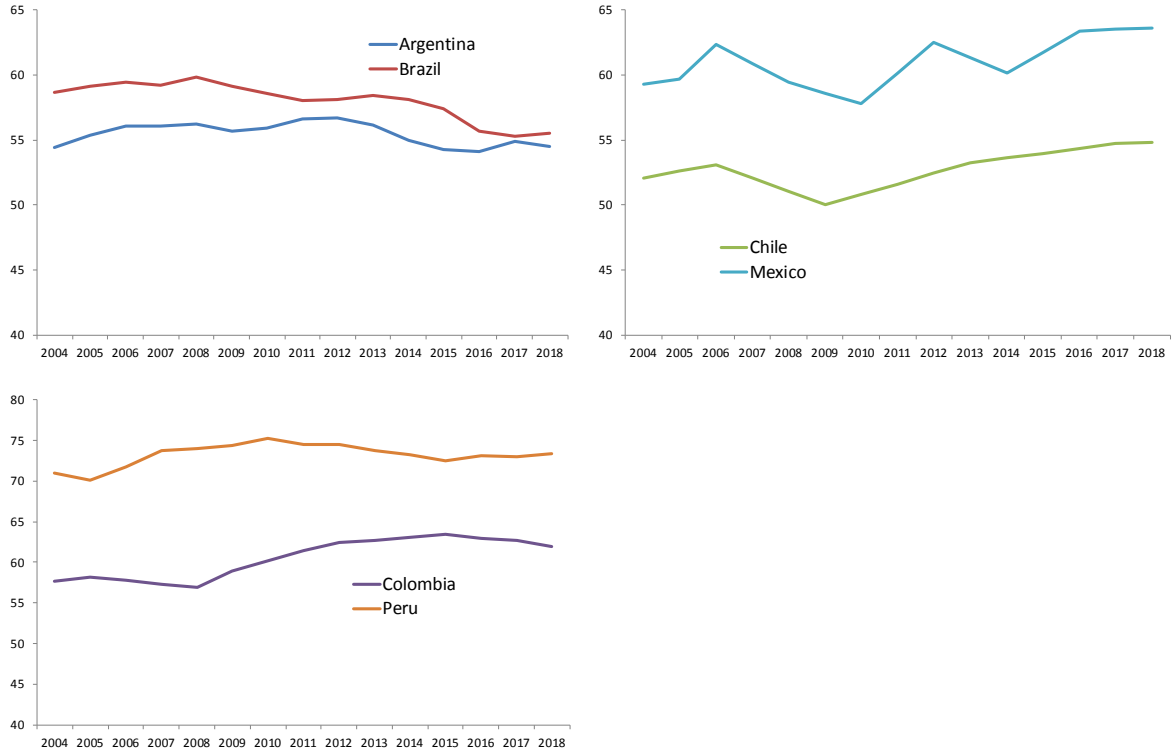
Source: own calculations based on PIACC and national household surveys of late 2010s.
Note: each grey line shows a different country.

Figure 4.5: Indices of routinization by region



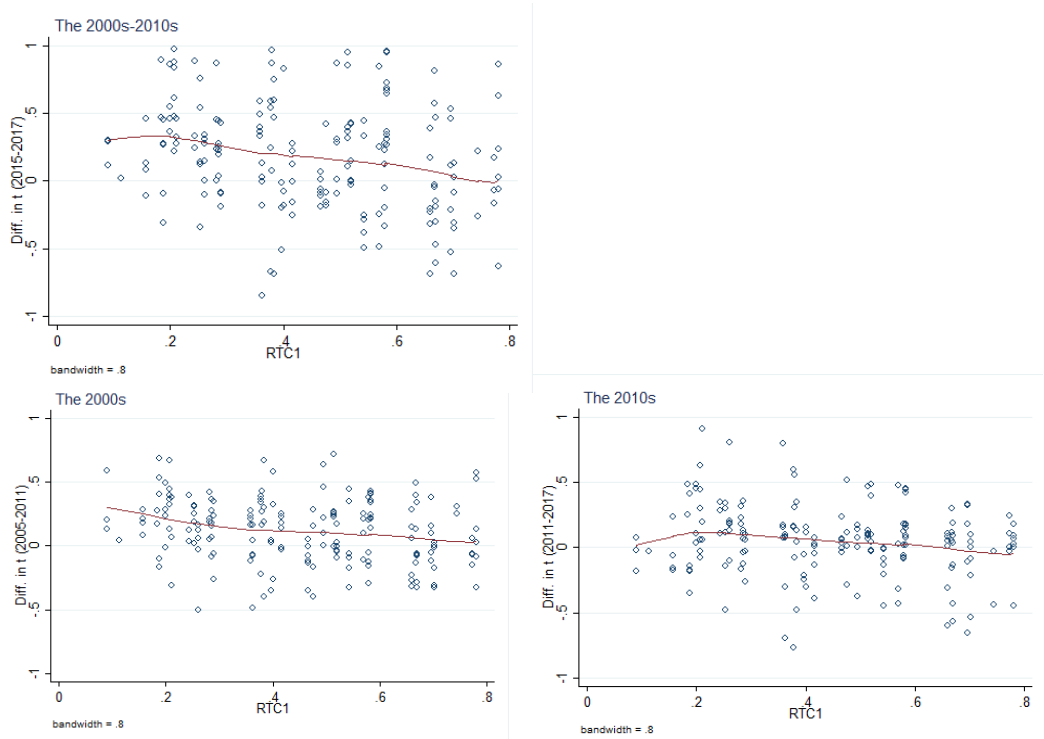
Source: own calculations based on PIACC and national household surveys of late 2010s.

Figure 4.6: Employment rate



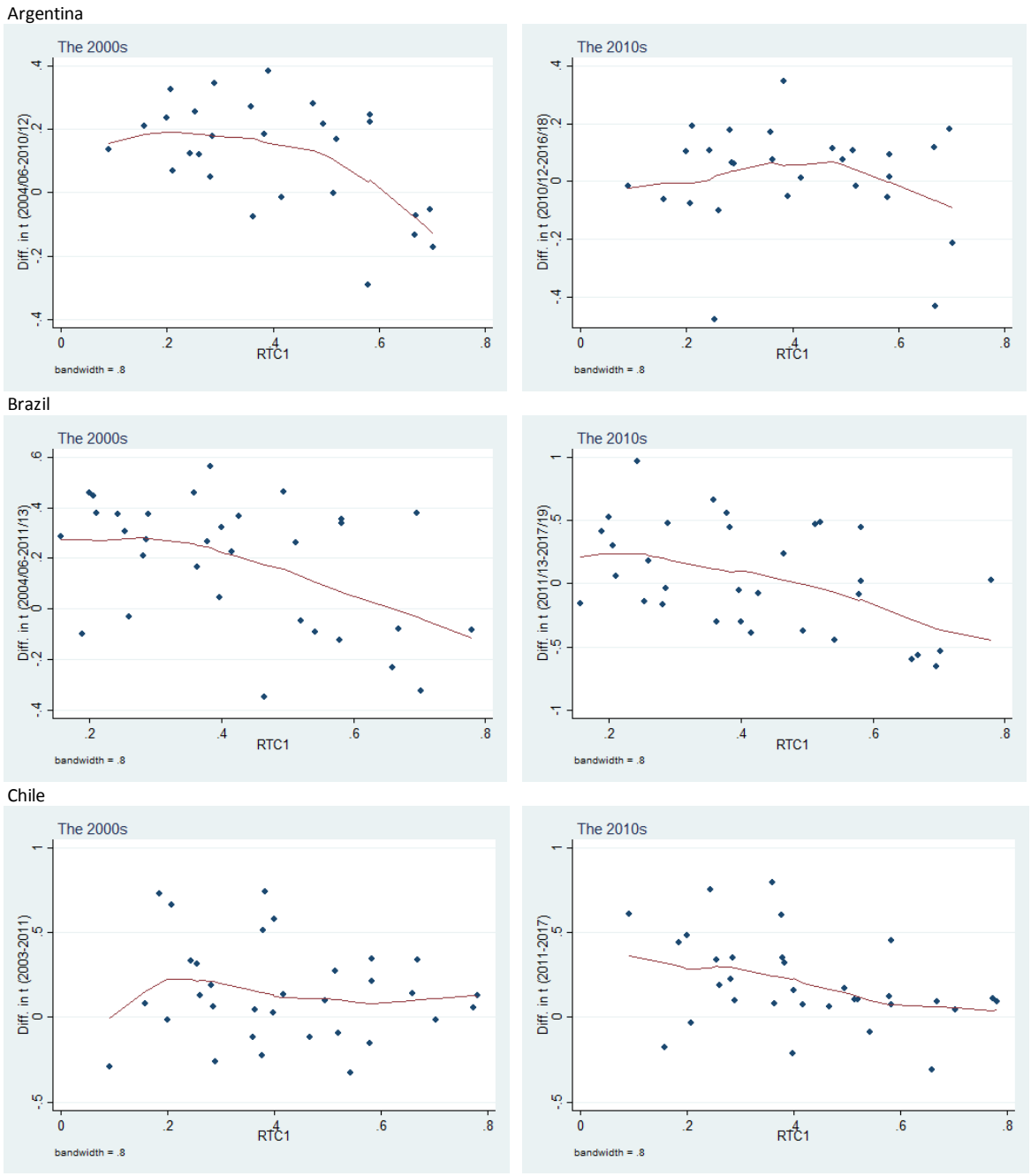
Source: own calculations based on national household surveys.

Figure 4.7: Growth rate in number of workers and routinization by occupation



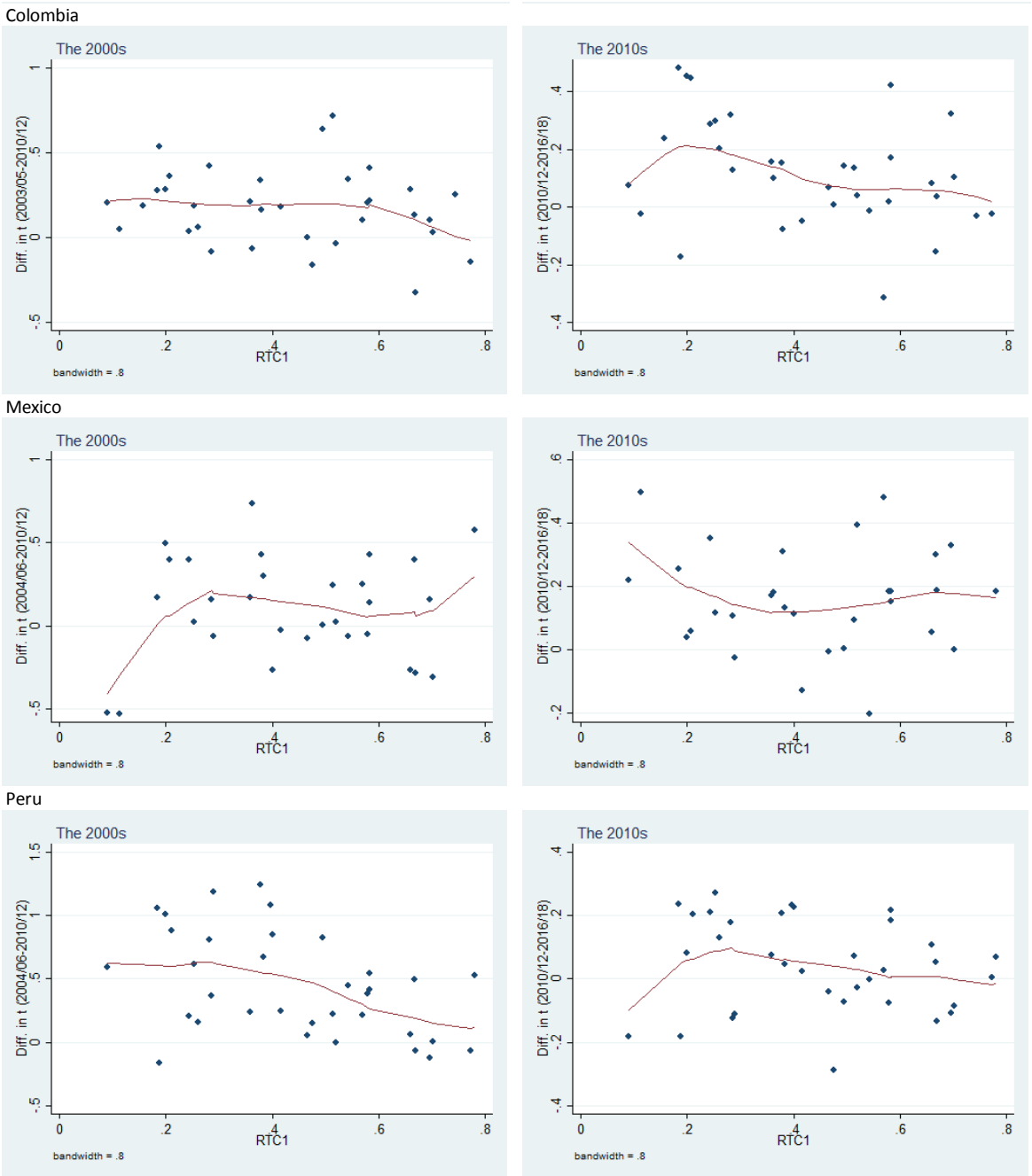
Source: own calculations based on PIACC and national household surveys.

Figure 4.8: Growth rate in number of workers and routinization by occupation



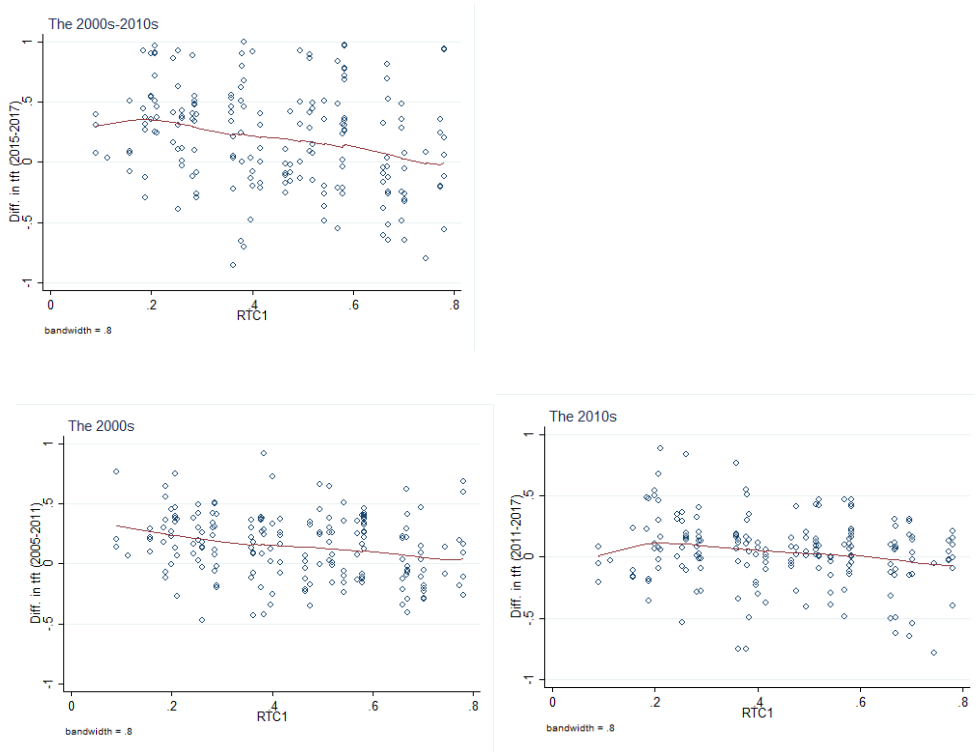
Source: own calculations based on PIACC and national household surveys.

Figure 4.8 (cont.): Growth rate in number of workers and routinization by occupation



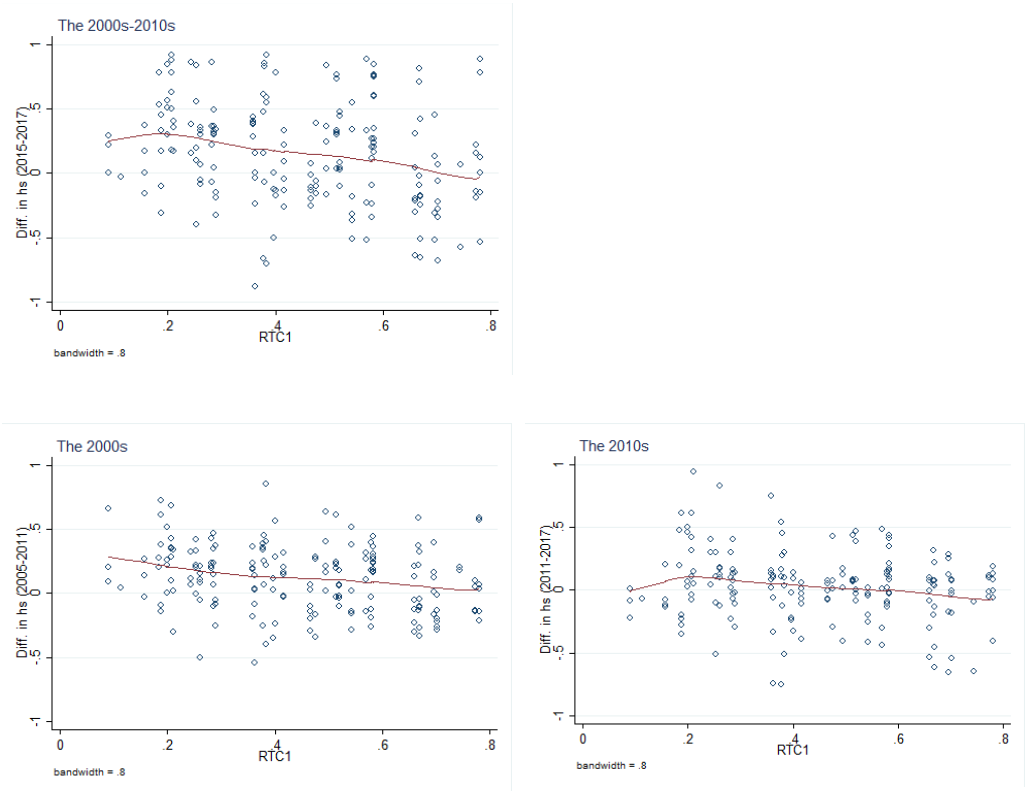
Source: own calculations based on PIACC and national household surveys.

Figure 4.9: Growth rate in full time-workers and routinization by occupation



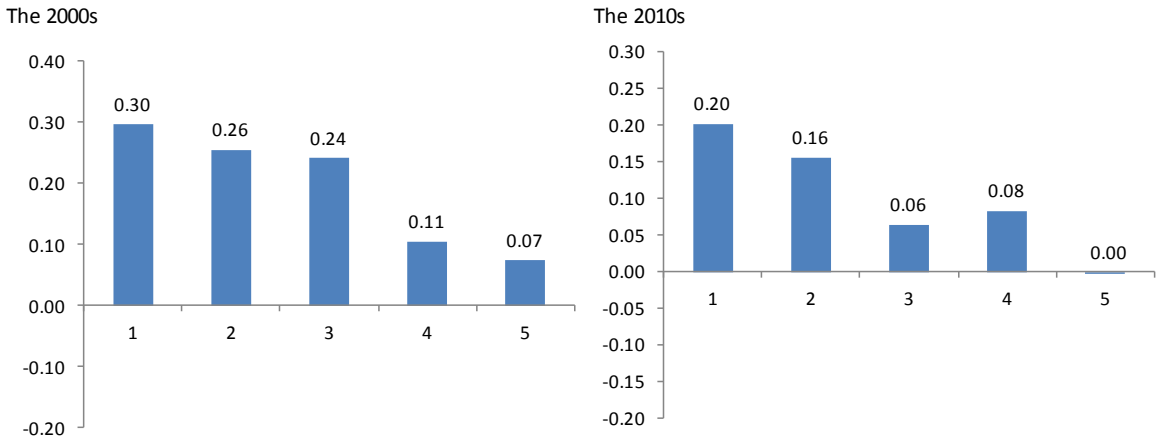
Source: own calculations based on PIACC and national household surveys.

Figure 4.10: Growth rate in hours of work and routinization by occupation



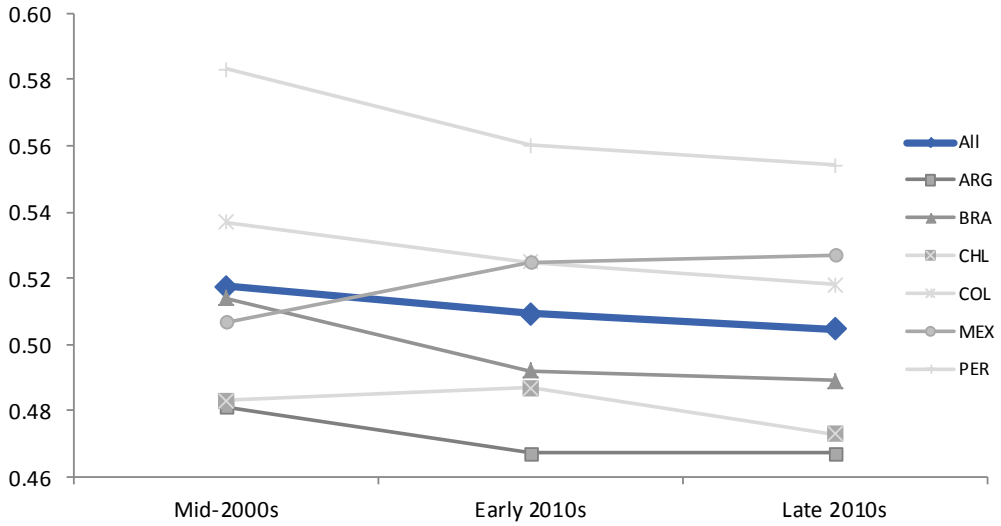
Source: own calculations based on PIACC and national household surveys.

Figure 4.11: Growth rate in number of workers by quintiles of RTC



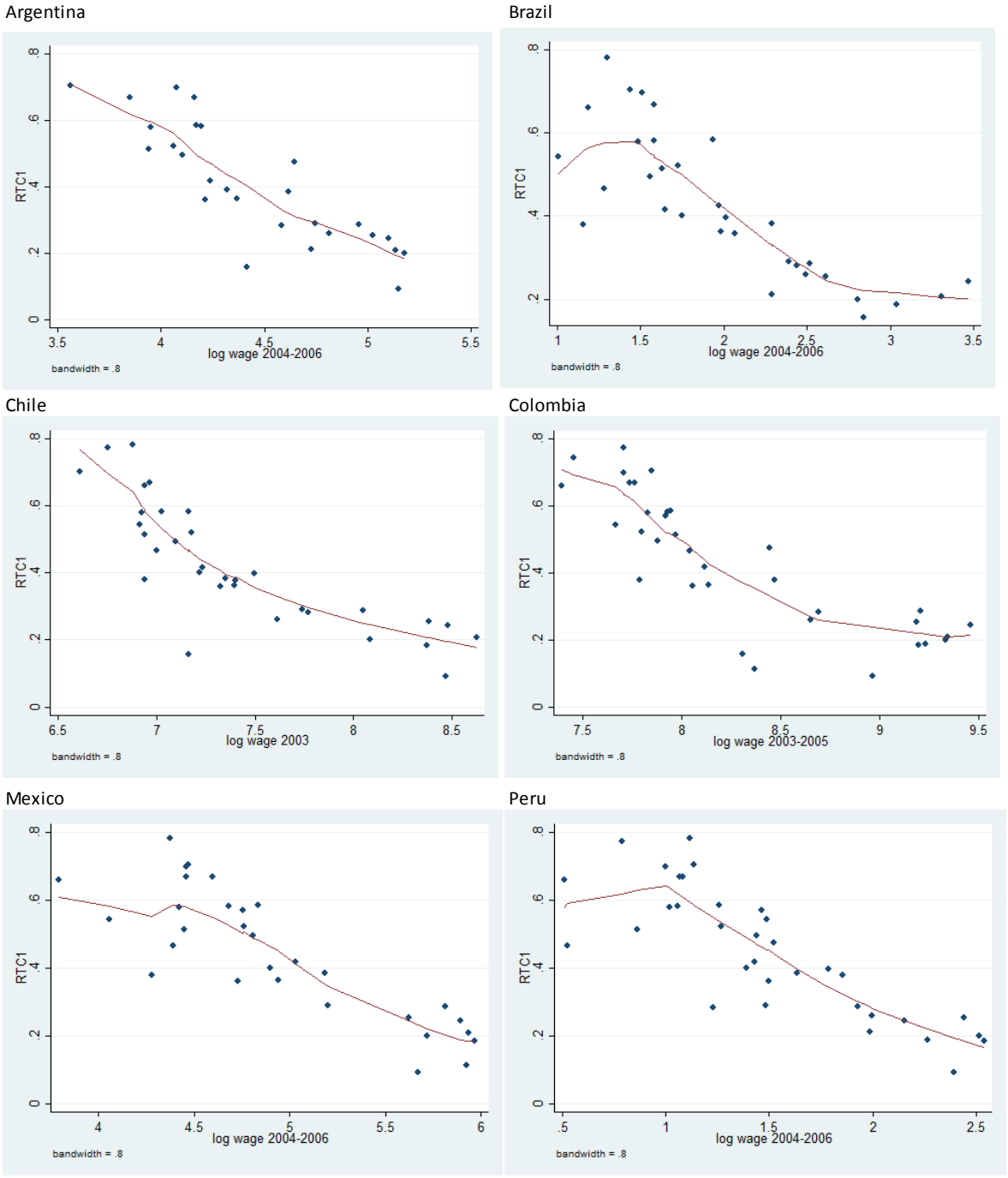
Source: own calculations based on PIACC and national household surveys.
Note. Occupations sorted by quintiles of RTC1 in the horizontal axis.

Figure 4.12: Indicators of routine task content
Mean for Latin America, over time



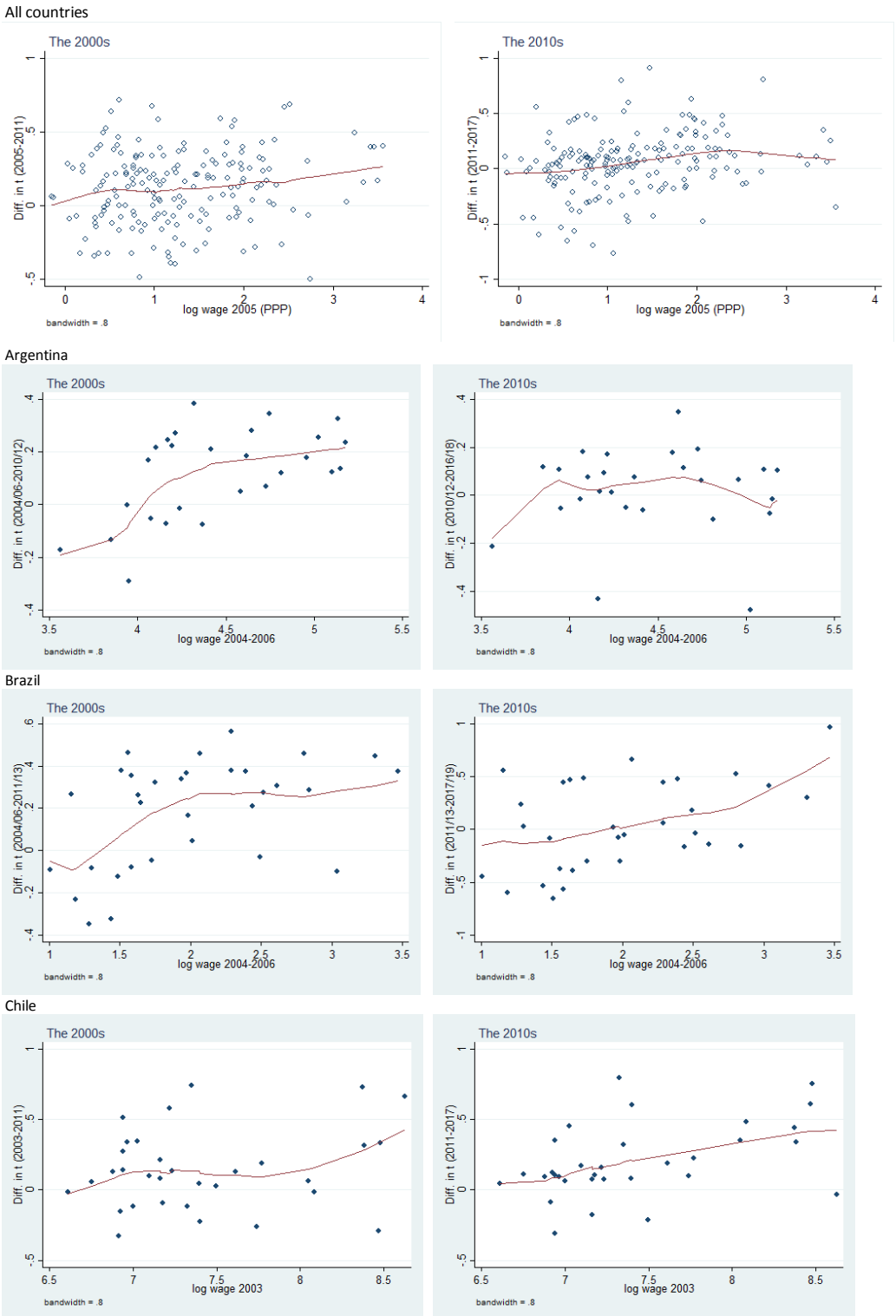
Source: own calculations based on national household surveys and PIACC.

Figure 4.13: RTC and initial wages by occupation



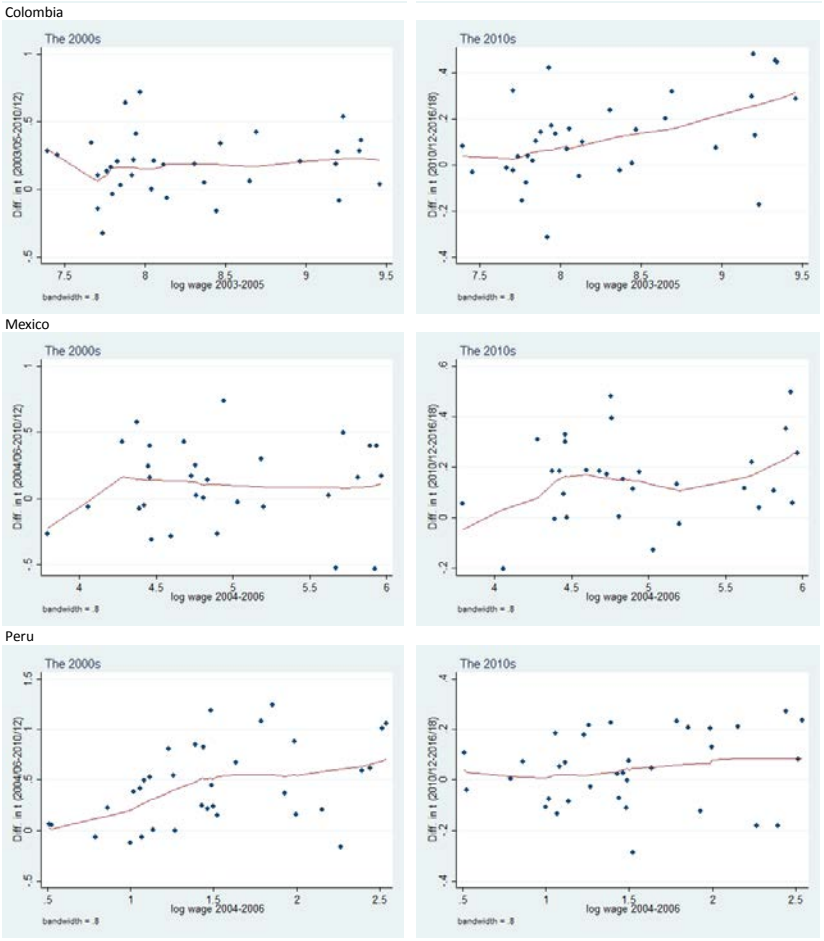
Source: own calculations based on national household surveys and PIACC.

Figure 4.14: Growth rate in number of workers and initial wage by occupation



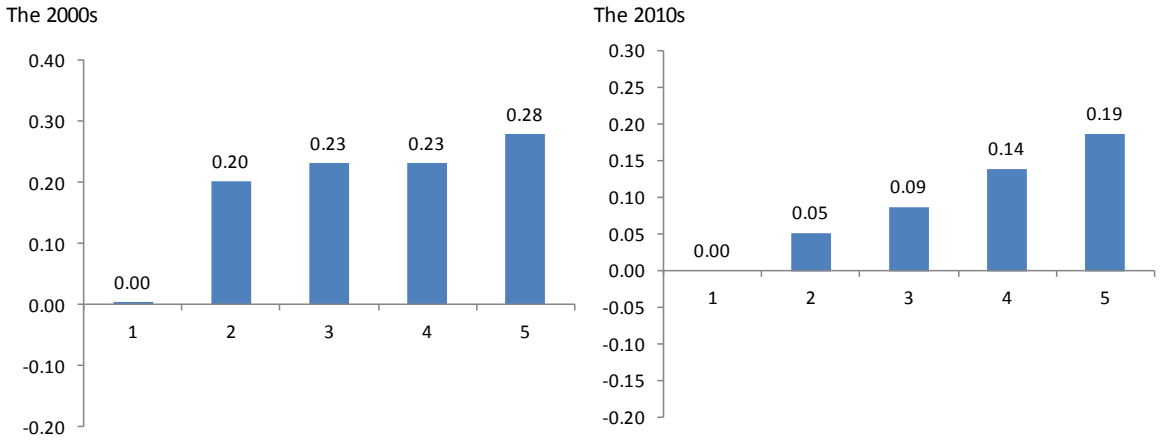
Source: own calculations based on national household surveys and PIACC.

Figure 4.14 (cont.): Growth rate in number of workers and initial wage by occupation



Source: own calculations based on national household surveys and PIACC.

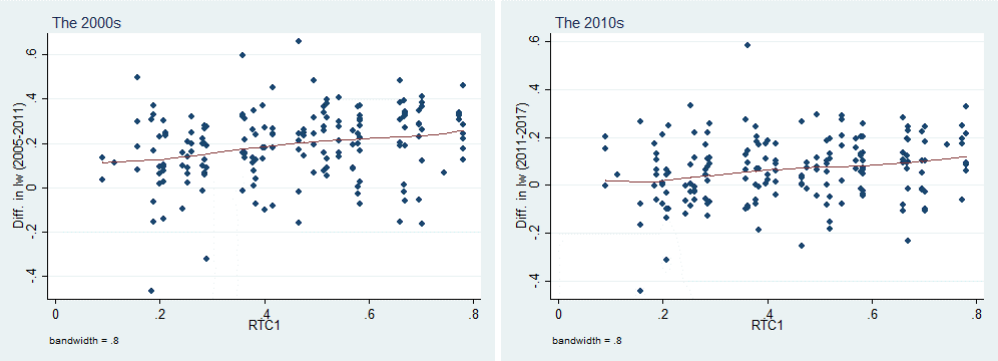
Figure 4.15: Growth rate in number of workers by quintile of initial wage



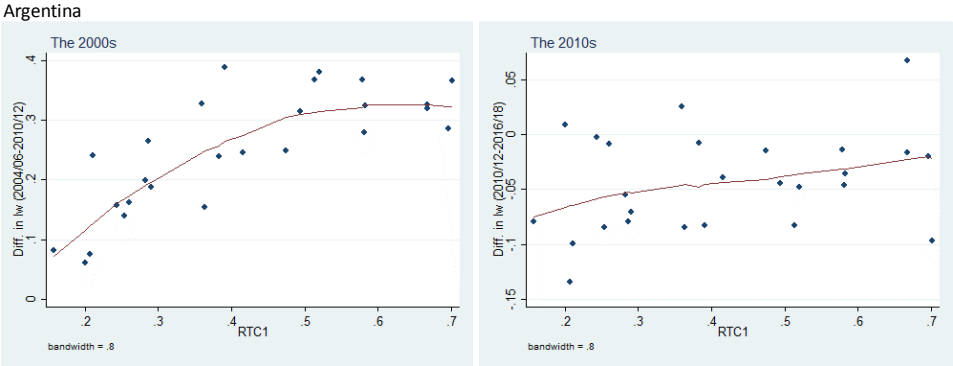
Source: own calculations based on national household surveys and PIACC.
Note. Occupations sorted by quintiles of initial wage in the horizontal axis.

Figure 4.16: Growth rate in mean real wages by degree of routinization

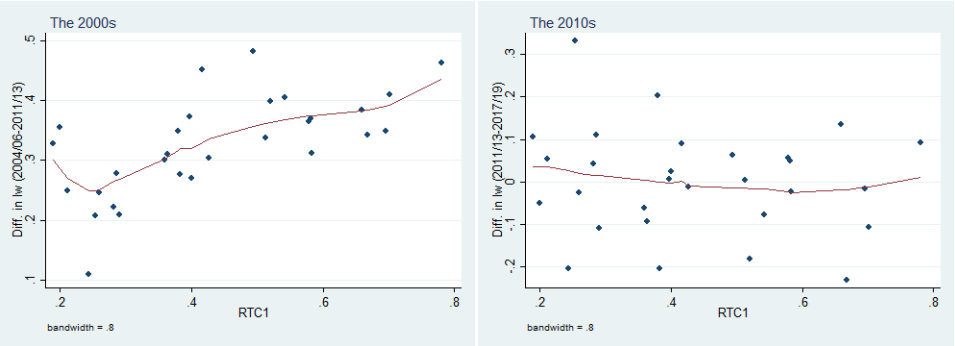
All countries



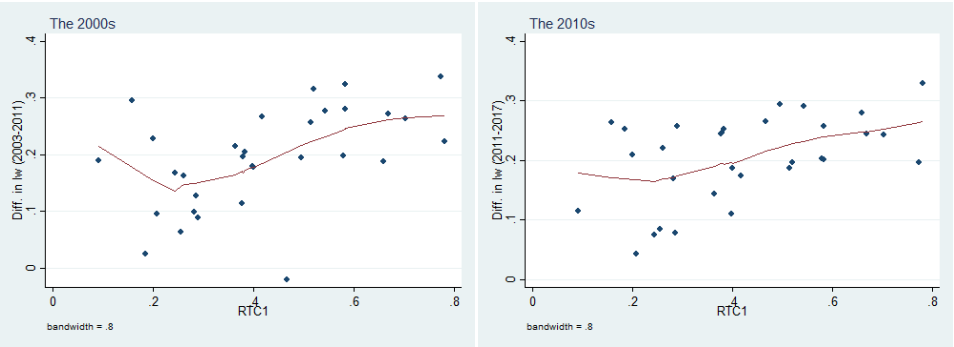
Argentina



Brazil

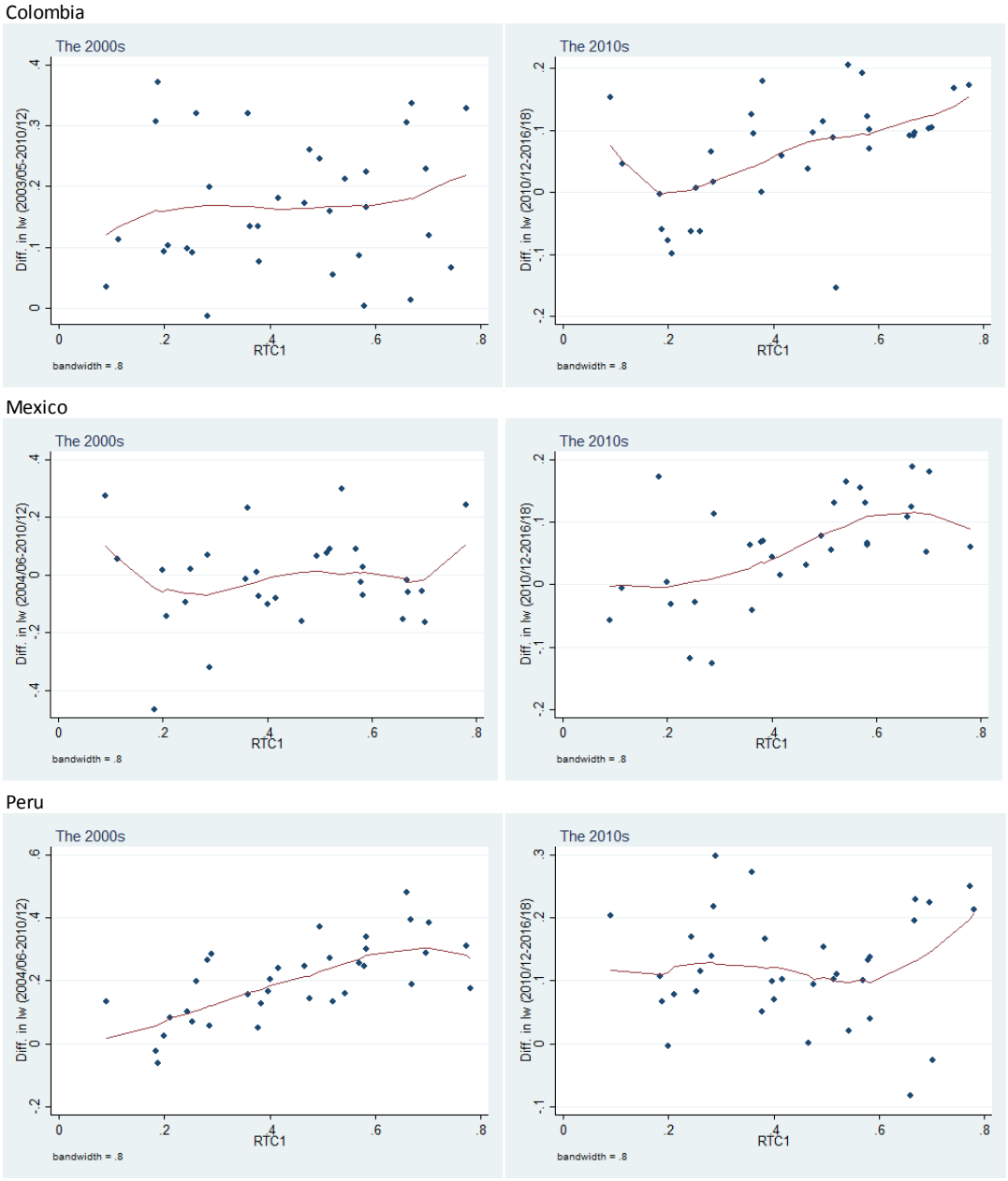


Chile



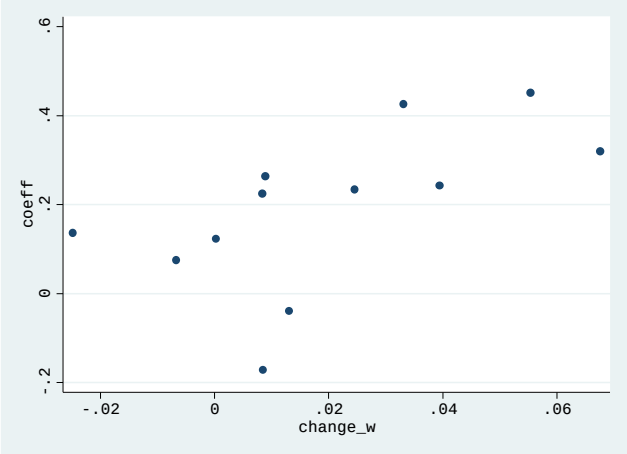
Source: own calculations based on national household surveys and PIACC.

Figure 4.16 (cont.): Growth rate in mean real wages by degree of routinization



Source: own calculations based on national household surveys and PIACC.

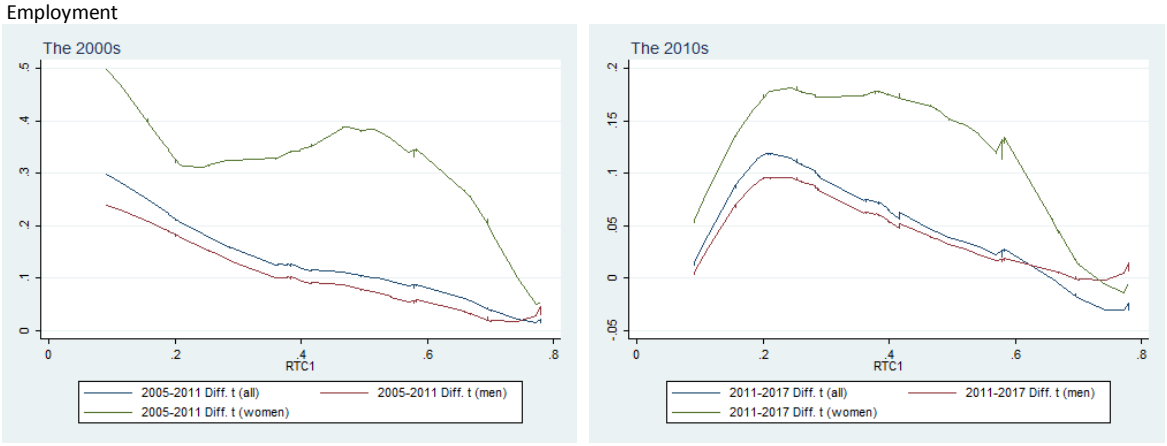
Figure 4.17: Coefficients in regression of wages changes on RTC and change in real wages



Source: own calculations based on national household surveys and PIACC.
Note: each point represents a combination country/period (the 2000s or the 2010s).
Horizontal axis: annual change in real wages during the period. Vertical axis: coefficient of regression of changes in wages on RTC.

Figure 5.1: Growth rate in number of workers by RTC and gender

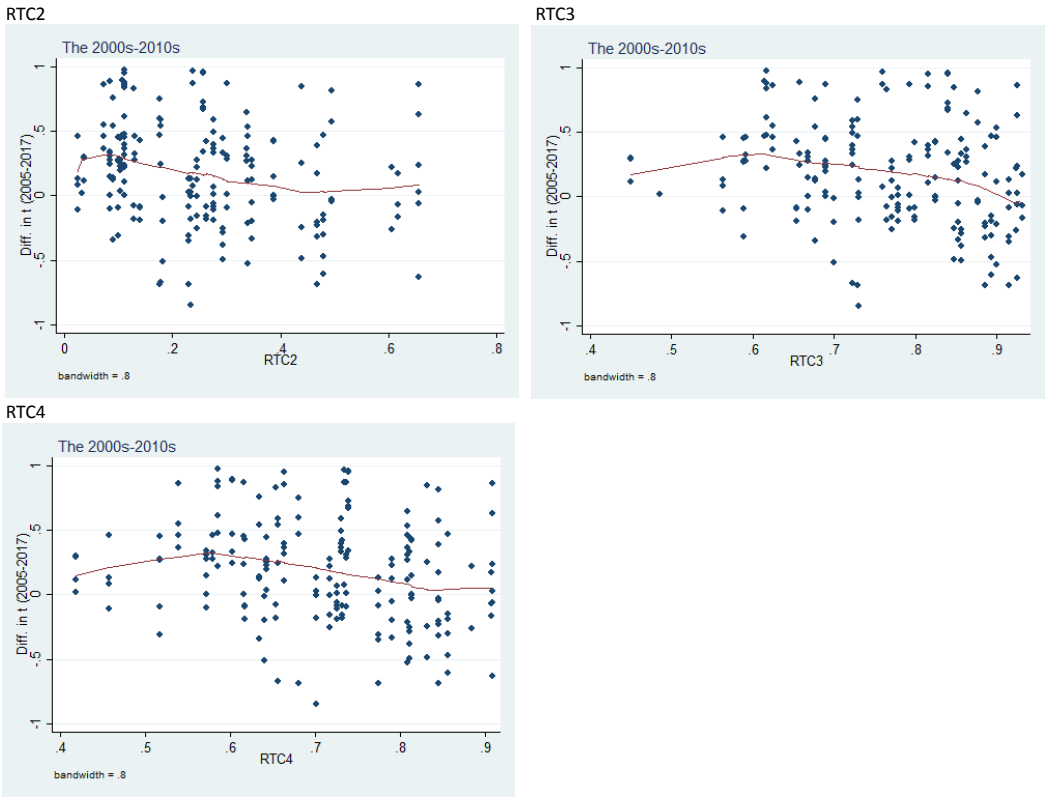
Employment



Hours of work

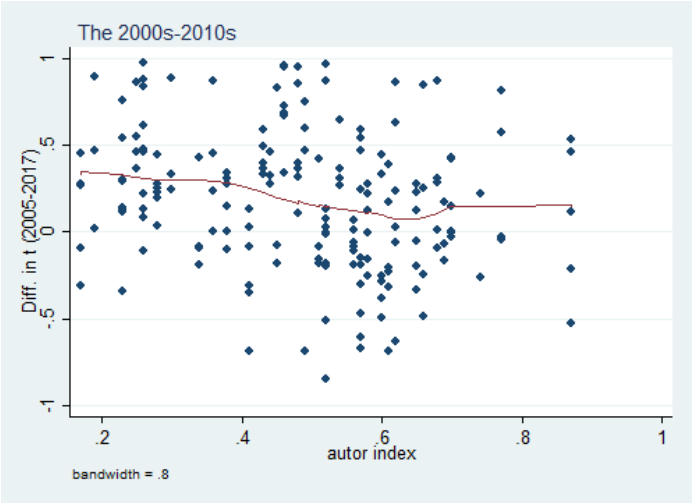
Source: own calculations based on national household surveys and PIACC.

Figure 6.1: Growth rate in number of workers and routinization. Alternative RTC indexes from PIACC



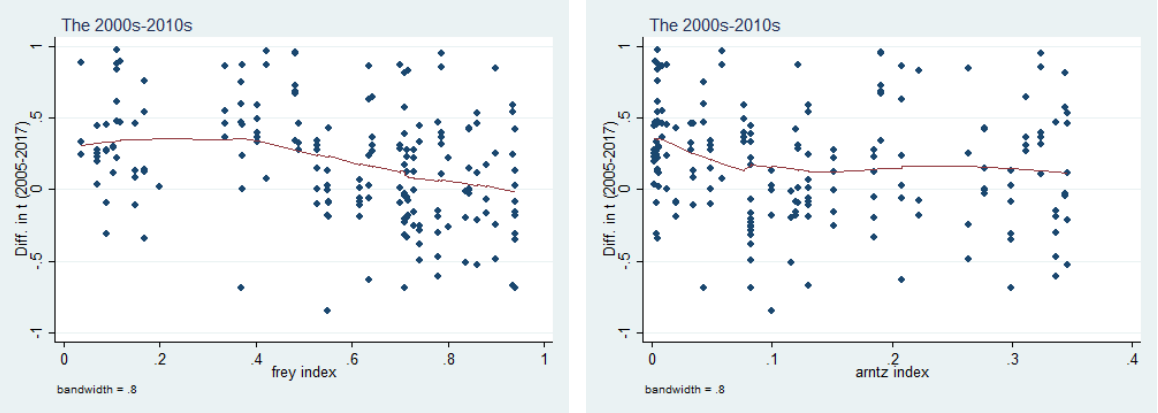
Source: own calculations based on national household surveys and PIACC.

Figure 6.2: Growth rate in number of workers and routine task intensity index of Autor and Dorn (2013).



Source: own calculations based on national household surveys.

Figure 6.3: Growth rate in number of workers and automatability by occupation. Alternative indexes



Source: own calculations based on national household surveys.

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About FoWiGS

The Future of Work in the Global South (FoWiGS) is an initiative supported by the International Development Research Centre (IDRC) and coordinated by the Center for the Implementation of Public Policies Promoting Equity and Growth (CIPPEC).

It aims at understanding the implications of technological change on jobs from a Global South perspective bringing data, knowledge, and policy frameworks to build evidence-based narratives on the future of work in developing countries.

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