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Changes in occupations and their task content

Implications for employment and inequality in Argentina, 2003–19

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Abstract: The aim of this paper is to identify the scope and patterns of the structural transformation as evidenced by changes in occupations and their task content, and their impact on employment, earnings and income distribution in Argentina during the new millennium. Results show that the changes in jobs did not follow the same pattern as those in earnings. In particular, earnings grew but employment shares fell in low-paying occupations. The macroeconomic conditions, production structure, and labour market institutions seem to shape the impact of technology on job demand and on earnings distribution. Overall, the findings point at the need for a broader perspective with a view to achieving a better understanding of the extent to which these factors may have affected the adoption of technology and the composition of employment in a country characterized by high economic instability and dramatic changes in their productive structure.

Key words: skills, tasks, polarization, inequality, Argentina

JEL classification: J24, D63, E24, N36

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1 Introduction

There is an intense debate worldwide on the impact of the ongoing technological change and task automation on the present and future nature of work. The discussion, however, is not novel. During the 1990s there was consensus on the skill-biased technological change, especially in developed countries. This was the canonical explanation regarding the expanding demand of high-skilled workers over low-skilled. This skill upgrading process was, in turn, a contributing factor to the rise in earnings inequality.

Recently, a new phenomenon has spread among high-income countries: middle-skilled jobs saw a decline over high- and low-skilled/low-wage occupations. This job polarization phenomenon has been mainly found in the United States (Wright and Dwyer 2003; Autor and Dorn 2013; Autor et al. 2006) and in some European countries (Goos et al. 2014; Sebastian 2018).

The leading explanation for the loss of middle-skilled jobs—based on a task content framework—lies with the automation of routine tasks (cognitive or manual), usually performed by medium-skilled workers, over 'abstract' tasks (linked to problem solving, creativity, etc.) or 'manual non-routine' tasks (requiring greater personal interaction, adaptability, etc.). Since routine tasks are located in the middle of the wage distribution and non-routine tasks are located at the top and bottom, the progressive labour-technology substitution generates a reduction in wages in the first group and an increase (or stability) in the group of workers located at both ends of the wage distribution (Goos and Manning 2007; Autor and Dorn 2013). The hollowing out in the middle segment of wage distribution as a consequence of the 'routine-biased technical change' would be an explanation for the rising wage inequality (Acemoglu and Autor 2011; Goos et al. 2014).

Job polarization, however, does not always entail earnings polarization. While Autor et al. (2006) have found that these two phenomena go hand in hand in the United States, Goos and Manning (2007) have accounted for job but not wage polarization in the United Kingdom. For the latter, the increase in the proportion of 'bad jobs' was concomitant with a drop in their earnings, even in comparison with middling occupations whose demand was falling. For these authors, the explanation lies in the following: on the one hand, displaced workers from routine jobs may be less skilled than those who remain in these occupations; thus, this 'composition effect' could account for the relative wage increase in the middle of distribution. On the other hand, the weakening in unionization and in minimum wages could also explain the fall in wages at the bottom half of the wage distribution.

Despite the increasing importance of these topics, the empirical literature for less developed countries—including Argentina—is scarce. Additionally, given that the composition of employment, the speed and type of technological adoption, the position of countries in global value chains, and the macroeconomic and productive conditions are very different across the globe, the results obtained for the developed world are not necessarily the same for developing or emerging countries.

The main aim of this paper is to evaluate the scope and patterns of the structural transformation as evidenced by changes in the composition of jobs and tasks in Argentina, and its impact on earnings and distribution.

This study makes three contributions to better understand the evolution of employment and inequality in Argentina. First, it thoroughly examines the changes in the composition of employment based on country-specific information on the job task content. Therefore, unlike

previous analyses on this topic in Argentina, this study does not assume that the task composition of jobs is the same as in developed countries.

Second, this study discusses the extent to which changes in occupations and job task content result in a polarizing pattern, taking into account the specific characteristics of the Argentine labour market.

Third, this paper evaluates the role of occupation and its content changes in shaping the evolution of earnings distribution. In this way, it contributes to the existing Argentine literature on inequality by adding a novel dimension.

The paper follows with the review of the literature on the evolution of income distribution and technological change in Argentina. Section 3 details the source of information and the econometric methodology. Section 4 presents an overview of the evolution of macroeconomics, labour market, and income distribution in Argentina. Section 5 analyses the changes in the composition of employment and evaluates the hypothesis of job polarization. Section 6 studies the trends in real earnings and assesses the hypothesis of earnings polarization. Section 7 evaluates the role of changes in occupations in shaping the evolution of inequality. Section 8 discusses all previous results in an integrated manner. Finally, Section 9 concludes.

2 Literature review

The impact of the technological change on inequality has been a widely studied topic in Latin America and, in particular, in Argentina in the 1990s. The broadly accepted argument on the worsening of the wage distribution was based on the so-called Unified Theory.[1] Starting from the canonical supply–demand framework applied to the labour market, this theory shows that an increase in the demand for high-skilled workers that exceeds its supply creates an excess demand for this group, thus enlarging education returns and worsening labour income distribution. This hypothesis is based on increasing openness of the economy and on the skill-biased technological change (Galiani and Sanguinetti 2003; Gasparini and Lustig 2011).

In addition to the influence of technological changes and trade opening, Argentine local conditions played an important role. In particular, the income distribution worsening over the 1990s was also a result of low dynamism in the aggregate labour demand and a persistent high level of unemployment partly determined by the economic disbalances during the currency board regime. High unemployment had a greater impact on less-educated people, both directly because of its higher relative incidence and indirectly because of its higher negative impact on their wages (Beccaria and Maurizio 2017; Damill et al. 2002). Weakened labour institutions, minimum wage, and collective bargaining were other factors associated with the increasing inequality over this decade (Cornia 2012; Trujillo and Villafañe 2011; Keifman and Maurizio 2012).

The more recent studies on the evolution of inequality in Argentina show a clear contrast between the 1990s and the 2000s. Overall, they have concluded that labour income can account for most of the increasing household income concentration throughout the 1990s as well as its subsequent decline in the 2000s (Beccaria et. al. 2015; Cornia 2012).

[1] Atkinson (2002) calls this process 'Transatlantic Consensus'.

Most of the studies that assess labour income changes, in turn, have shown that the main factor behind the reduction in income inequality during the 2000s was the drop in the returns to education, which had also been the cause for higher inequality levels in the previous decade (Alejo et al. 2014, 2015; Cornia 2012; Lustig et al. 2013; Gasparini et al. 2011).

As to what triggered those changes in the returns to education, some studies have put emphasis on the interaction between the relative supply and demand for qualifications. Gasparini and Cruces (2010) have highlighted a slowdown in the rate of technology incorporation during the 2000s within a context of a growing relative supply of skilled workers. According to their view, following the overshooting in inequality of the previous decade resulting from the rapid incorporation of technology, it is reasonable to expect an adjustment phase, which might have also contributed to the equalizing trends of the 2000s.

Other studies have pointed out that both the implementation of income policies immediately after the macroeconomic crisis in 2001/02 and the strengthening of labour institutions might have also played a part in reducing the income gap among workers with different skills and educational levels. Maurizio and Vázquez (2016) and Casanova and Alejo (2015) have highlighted the strengthening of the minimum wage and collective bargaining as contributing factors to the improvement of wage inequality, both in Argentina and in other countries in the region.

The reduction of labour informality observed in many Latin American countries during the 2000s has also positively impacted on labour income inequality. Beccaria et al. (2015), Maurizio (2015), and Maurizio and Vázquez (2015) have found an equalizing impact of the formalization process in Argentina. This finding is in line with those encountered in other Latin American countries (Amarante and Arim 2015).

Few studies, however, have addressed the impact of automation on the structure of employment and inequality in Latin America and in Argentina during the new millennium. The results are non-conclusive.

Maloney and Molina (2016), by means of census data, have analysed the evolution of employment across occupational groups in 21 developing countries in Africa, Asia, and Latin America (Brazil, the Dominican Republic, Ecuador, El Salvador, Mexico, Nicaragua, Panama). Overall, they have not found strong evidence of polarization in these countries. However, Brazil and Mexico have shown a relative fall in the category 'operator', which could suggest a potential polarizing pattern.

Messina et al. (2016) have also examined the pattern of occupational changes in Brazil, Chile, Mexico, and Peru over the 2000s. Except for Chile, the results are not consistent with the polarization hypothesis. In particular, in the three remaining countries, employment share in the middle and high end of the income distribution increased while low-paying occupations declined substantially. From this evidence, Messina and Silva (2018) have concluded that polarization patterns may not have yet got to Latin America perhaps because of barriers to technology penetration.

Brambilla and Tortarolo (2018), who use Argentine company-level data, have shown that the adoption of information and communications technology leads to a wage and productivity increase, particularly for high-productivity firms that employ high-skilled workers. In turn, such adoption induces a lower relative demand for low-skilled employment, although in absolute terms it stimulates job creation in all skill categories (this effect is greater in fast-growing companies).

Finally, Apella and Zunino (2017) have analysed the employment composition trends in Argentina and Uruguay over the last 20 years. Assessing the task content from the US Occupation

Information Network (O*NET) survey, they point out that cognitive tasks significantly increased while manual tasks decreased in both countries. More recently, Apella and Zunino (2021), also based on the information provided by O*NET, have studied labour trends according to job task content in nine countries in Latin America and the Caribbean between the mid-1990s and 2015. They have found an increase in the relative importance of cognitive tasks to the detriment of manual tasks.

Based on all the findings mentioned above, this study seeks to further the understanding of the structural change in the employment composition and inequality in Argentina by analysing the links between occupations, task content, and earnings distribution.

3 Data, definitions, and methodology

3.1 Data

The microdata used in this paper comes from the *Encuesta Permanente de Hogares* (EPH), a survey carried out by Argentina's National Institute of Statistics and Censuses (INDEC). This survey collects detailed information on jobs, income, and socio-demographic characteristics of the population. The survey is carried out on a quarterly basis and covers 31 urban centres accounting for 62 per cent of the total population and for 67 per cent of the urban population. As it does not cover rural areas, agricultural workers were left out from the analysis.

The period studied is between 2003 and 2019, in particular, the fourth quarters of each year in order to avoid potential seasonality problems. The selection of these years is based on the availability of comparable data. Also, this is a period characterized by economic growth and inequality reduction but, at the same time, by marked business cycles and significant changes in labour market institutions. Therefore, the selected time period makes it possible to assess to what extent these trends may have affected the adoption of technology and the composition of employment.

We work with all workers of working age (15–64 years), and with paid employee exclusively as well. To reduce the influence of outliers on labour incomes, the top 1 per cent was excluded. The income concept used is earnings from the main occupation. It includes net cash earnings from salaried and independent workers. In particular, we use weekly earnings from the transformation of the monthly earnings enquired in the survey.

3.2 Occupational coding

Argentina has its own national occupational classification (CNO-01). Therefore, it was necessary to adapt the CNO-O1 to make it compatible with the International Standard Classification of Occupations (ISCO). To that end, we matched the five-digit CNO-01 with the two-digit ISCO-08, using the crosswalk built by INDEC (2018). Then, we matched ISCO-08 to ISCO-88 (both at the two-digit level) using the crosswalk made by the International Labour Organization.[2]

[2] We map ISCO-08 to ISCO-88 for comparability with other country studies included in this project.

3.3 Routine task content measures

To analyse the task content of each occupation, we need information on the different types of activities carried out by workers on the job. Autor et al. (2003) classify tasks considering two dimensions: routine/non-routine, and manual/cognitive. According to this classification, routine tasks are those characterized by a set of repetitive actions that can be accomplished by following explicit rules. On the contrary, non-routine activities are those changing in time. Manual tasks demand physical activities while cognitive tasks are those requiring information processing, programming, creativity, and problem solving.

Occupations involve a combination of different types of tasks. In order to study patterns and trends of job task content in Argentina, we use a routine-task intensity (RTI) measure based on previous literature (Autor and Dorn 2013; Goos et al. 2014). Following Lewandowski et al. (2020), the RTI is a composite measure based on four constructed task measures shown as follows:

$$RTI = ln\left(\frac{r_{cognitive} + r_{manual}}{2}\right) - ln\left(\frac{nr_{analytical} + nr_{personal}}{2}\right) \quad (1)$$

where $r_{cognitive}$ represents routine cognitive tasks, r_{manual} routine manual tasks, $nr_{analytical}$ non-routine cognitive analytical tasks, and $nr_{personal}$ non-routine cognitive personal tasks. In particular, the measurement of the non-routine cognitive analytical task is based on solving problems, programming, and reading journals, while the measurement of non-routine cognitive interpersonal task is based on supervising others and presentations. The routine cognitive task measure is based on the ability to change the order of tasks, filling out forms, and so on. Finally, the measurement of manual task is based on the performance time of physical activities involved in a job. This definition omits non-routine manual tasks from the analysis used in the original approach by Autor and Dorn (2013). According to Lewandowski et al. (2017), routine and non-routine manual tasks tend to be highly correlated.

Previous empirical studies on job task content have relied on the O*NET survey, since data on this have only recently become available for a larger group of countries. However, the task composition of occupations in Argentina, and in general in developing countries, might differ significatively from those in developed countries. In particular, differences in labour productivity, technology and skills could mean that the same job requires different skill sets across countries. Therefore, task content is currently being assessed in countries other than the United States. An example of this is the Survey of Adults Skills within the framework of the Programme for the International Assessment of Adult Competencies (PIAAC) conducted over 40 countries. Other examples are the Skill Measurement Program (STEP), implemented by the World Bank in 17 low- and middle-income countries, and the China Urban Labor Survey (CULS) carried out by the Chinese Academy of Social Sciences, which covered six cities in 2016.

None of these initiatives included Argentina, nor has the country carried out a survey of its own on this dimension. For this reason, the present study is based on the estimation of the country-specific RTI (CS-RTI) by occupation built by Lewandowski et al. (2019, 2020). With data collected in 47 countries through PIAAC, STEP, and CULS, including low-, middle- and high-income countries, they performed a regression-based estimate to evaluate the role of four variables in order to predict the task content of jobs across countries: technology, globalization, structural change, and skill supply. Based on these findings, Lewandowski et al. (2019, 2020) predicted CS-RTI for several countries, including Argentina. This measure takes into account the gross domestic product (GDP) per capita, the information and communications technology capital stock, and the trade and regional fixed-effects. Then, Argentina's estimated RTIs are merged at the two-digit ISCO-88

to the EPH data. Therefore, unlike in previous analyses on job polarization in Argentina, this study does not assume that the task composition of jobs is the same as in developed countries.

Despite the aforementioned limitations and for the sole purpose of having a reference, we also use the RTI measure shown in Equation (1) based on O*NET data (O*NET RTI).

3.4 Other relevant variables

In addition to the occupation categories and the routine task content measures, the analysis incorporates other relevant variables, among them the level of education. We differentiate four levels of education: no formal education, primary complete, secondary complete, and higher education complete. Other dimensions included are gender and nationality (in particular, to record the native versus immigrant condition).

In order to consider the geographical heterogeneity existing in the country, we distinguish among six regions: Greater Buenos Aires, North-West, North-East, Patagonia, Cuyo, and Pampeana.

Finally, informality is another key dimension in the Argentine labour market. Here, we use the concept of *informal economy* that combines the legal approach (informal employment) with the productive approach (informal sector). Following ILO (2018) recommendations, employment in the informal economy is made up of wage earners whose employers do not make payroll deductions to pay social security contributions, salaried workers and employers in enterprises with fewer than five employees, and non-professional own-account workers.

3.5 Test for job and income polarization

To test the existence of job polarization, we follow the model proposed by Goos and Manning (2007):

$$\Delta \log E_{i,t} = \beta_0 + \beta_1 \log(w_{j,t-1}) + \beta_2 \log(w_{j,t-1})^2 \qquad (2)$$

where $\Delta \log E_{i,t}$ is the change in the log employment share of occupation *i* between t–1 and t (2003–19, 2003–12, 2012–19) and $\log(w_{j,t-1})$ and is the (log) mean weekly earnings in *t*–1.

A polarization pattern involves a negative first (linear) coefficient followed by a positive quadratic coefficient.

The same exercise has been done but with earnings, $\Delta \log w_{i,t}$ instead of job as the dependent variable (Sebastian 2018). To avoid any bias due to small jobs driving dominating results, both equations were estimated by weighting each occupation by its initial employment share.

3.6 Shapley decomposition

In order to decompose trends in earnings inequality measured by the Gini index into the contribution of changes within and between occupations, we follow the Shapley decomposition proposed by Shorrocks (2013). Since Gini is not additively decomposable, we estimate the contribution of inequality within and between jobs to the overall Gini index like the average contribution of each component over the two possible paths in which they can be estimated [see Equation (3)].

$$G = G_B + G_W \tag{3}$$

$$\text{with } G_B = \frac{1}{2}[G(y_b) + G - G(y_w)] \text{ and } G_W = \frac{1}{2}[G(y_w) + G - G(y_b)]$$

where y_b is a vector where individual worker earnings are the average earnings in their occupations (within-occupation inequality is removed), and y_w is a vector where worker earnings are such that all occupations have the same average earnings (between-occupation inequality is removed).

Then, changes in the Gini index can be decomposed into the contribution of each component.

3.7 Assessment of the role of routine task content in shaping earnings inequality

Finally, to evaluate the impact of changes in the routine task content on earning distribution during the period under analysis, we employed the Firpo et al. (2007, 2011) approach. This is an extension of the decomposition method developed by Oaxaca (1973) and Blinder (1973). The most salient advantage of this procedure over Oaxaca–Blinder is its flexibility regarding the specifications of the underlying wage model and quantification of the partial effects of changes in the distribution and in the returns of the covariables over other functionals (v) besides the mean.

The decomposition method has two stages: (i) the estimation of the aggregate composition and earning structure effects by employing a reweighting procedure; and (ii) the disaggregation of those effects into the individual contribution of each attribute using regressions on the recentred influence function (RIF) of the distributional statistic of interest.[3]

This methodology is applied to decompose changes in weekly earnings inequality between 2003–19, 2003–12, and 2012–19.

4 The erratic evolution of the Argentine macroeconomic context, labour market and income distribution over the 2000s: an overview

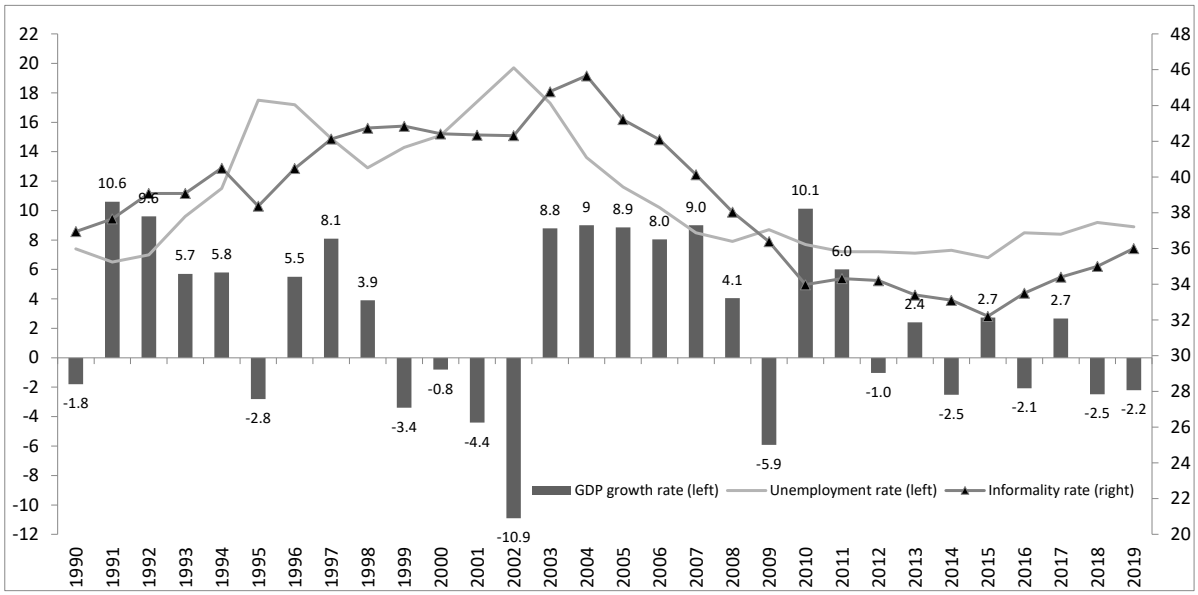
Argentina is characterized by high records of macroeconomic instability, which not only renders the process of adopting technology and automation slower but also can generate significant disruptions to the productive structure and labour market composition. Therefore, in order to contextualize the findings on occupations and earnings, our analysis begins with an overview of the Argentine macroeconomic and labour market performance during the new millennium.

Argentina faced its deepest macroeconomic crisis in history by late 2001 when the exchange rate regime (Convertibility Plan)[4] in effect during the 1990s collapsed. Argentina's GDP dropped 11 per cent in 2002, with an aggregate reduction of 20 per cent from mid-1998. By the second half of 2002, however, the economic recovery was also very fast. From 2003 to 2007, the annual GDP growth rate was 8–9 per cent (Figure 1).

[3] Further details in Appendix A.

[4] For further details about the Convertibility Plan, see Damill et al. (2002).

Figure 1: GDP growth rate, unemployment rate, and informality (1990–2019)



Source: authors' elaboration based on INDEC and EPH.

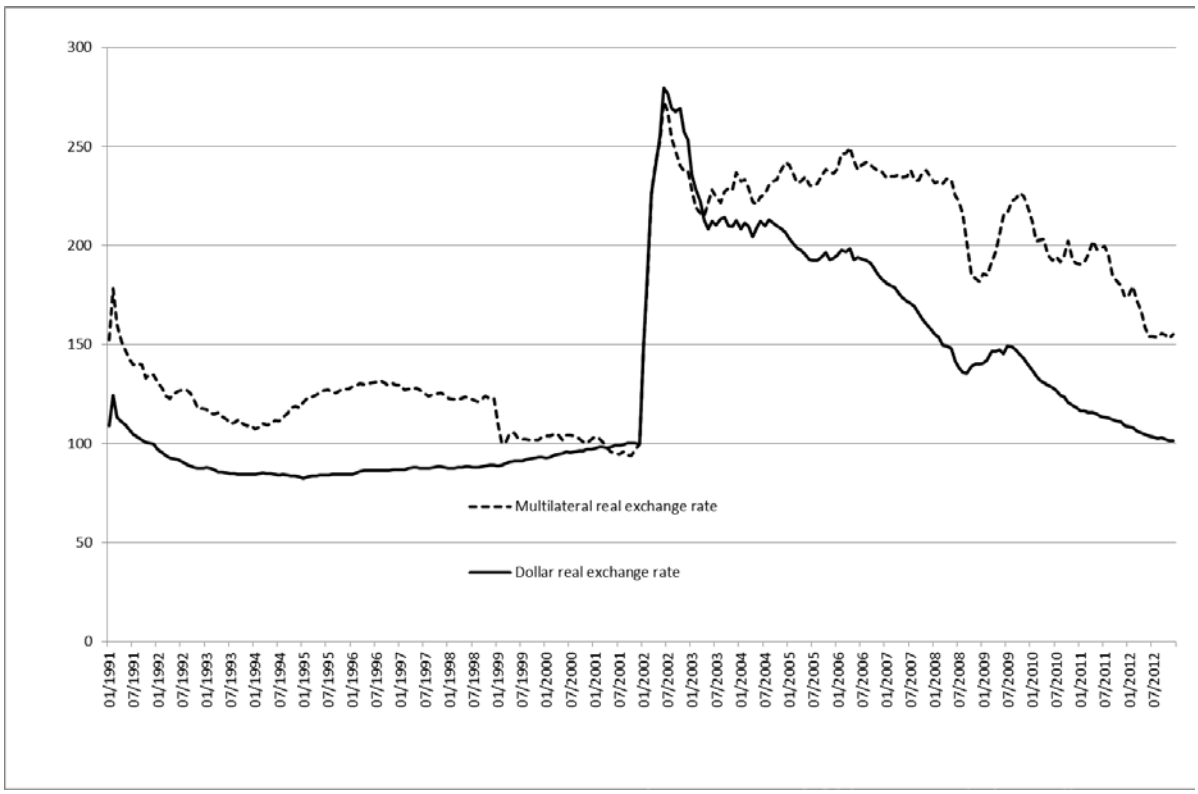
The consolidation of this growth path was to a great extent based on a favourable international context, which also characterized other South American countries during this same period. In particular, the sharp increase in the value of exports was due to the rise in the average price of export goods as well as the increase of quantities. This price rise resulted from the expansion of some Asian emerging markets, such as China and India, which constitute significant markets for Latin American products (Ocampo 2007). In the case of Argentina, the international price of soybean and other grains, which have a significant weight in the export basket, showed an upward trend all throughout the 2000s.

The higher real average exchange rate (Figure 2) was another crucial factor behind the rapid and intense output recovery after the 2001–02 crisis, since it allowed greater competitiveness in the tradable sectors. In fact, several belonging to the manufacturing industry that had been negatively affected in the period of trade opening and exchange rate appreciation initiated a process of import substitution while exports also showed a good performance.

The macroeconomic policies of the post-convertibility period, however, turned out to be erratic. In 2006, the first signs of policy mismanagement appeared as public spending started to grow faster than public revenues, this within a context of growing external deficit; but the economy continued expanding until 2009 when the annual GDP fell by about 6 per cent as a result of the international crisis. Although the economy grew again during 2010 and 2011, since 2012 there has been a significant weakening of the macroeconomic context. From that year on, economic instability became more evident showing years of slight growth alternated with years of recession. In 2018, the latest available data, the fall in GDP was 2.5 per cent.

Over these years, domestic inflation accelerated reaching 18 per cent in 2007, compared with rates that oscillated around 10 per cent in the 2005–06 period. Since 2010 annual inflation rates fluctuated around 25 per cent, reaching a peak of 47 per cent in 2018. As a consequence, a gradual and continuous real appreciation trend of the peso was verified during these years (Figure 2).

Figure 2: Multilateral real exchange rate and bilateral real exchange rate to US dollar (index December 2001=100)



Source: authors' elaboration based on Central Bank of Argentina data.

The different macroeconomic phases also had an impact on job creation and the composition of employment. The economic dynamism during the first years after the collapse of the Convertibility Plan led to a rapid expansion of the aggregate employment (at a pace that even surpassed output growth), to an improvement in the quality of the new occupations, and to an increase in real mean wages. In particular, the positive performance of labour market variables took place mainly between 2003 and 2008–10 where the unemployment rate declined from 20 per cent to 8 per cent, and labour informality among paid employees fell by 10 percentage points (pp) (Figure 1). After that point, however, all these labour improvements slowed down, stagnated, or began to reverse.

Along these years, Argentina also witnessed a process of reducing inequality, breaking the upward trend verified during the 1990s. However, in parallel to macroeconomic and labour market changes, earnings distribution showed strong movements over the 2000s. In particular, it is possible to identify two different phases both among paid employees and all workers: (i) 2003–12, when inequality fell (Gini index fell by about 6 pp); (ii) 2012–19, when earnings distribution worsened, after a sub-period of relative distributive stability between 2012 and 2015. However, since the first process was not fully reversed by the distributive worsening of the second phase, in 2019 the Gini coefficient was about 4–5 pp lower than in 2003 (Table 1).

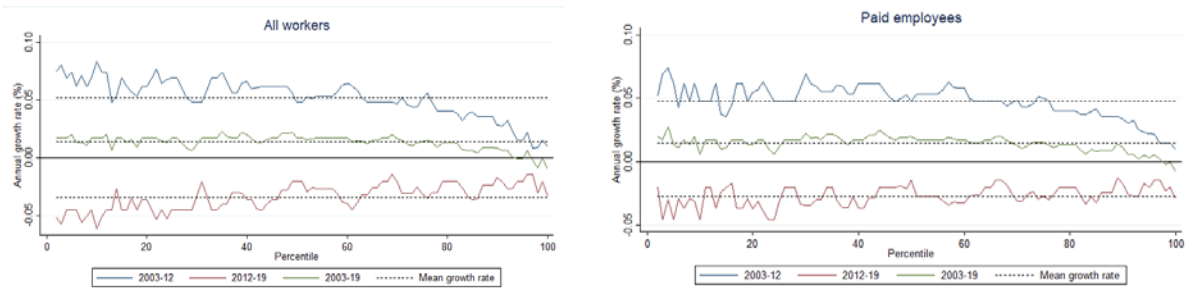
Table 1: Inequality indicators

	2003	2006	2009	2012	2015	2019
All workers						
Var (log earn)	0.84	0.78	0.73	0.63	0.65	0.74
Gini (log earn)	0.063	0.059	0.055	0.051	0.053	0.057
Gini (earn)	0.41	0.40	0.37	0.35	0.35	0.367
Paid workers	2003	2006	2009	2012	2015	2019
Var (log earn)	0.70	0.69	0.63	0.58	0.58	0.62
Gini (log earn)	0.06	0.05	0.05	0.05	0.05	0.05
Gini (earn)	0.39	0.37	0.35	0.33	0.33	0.34

Source: authors' elaboration based on EPH.

The pro-poor growth during the first phase and the inequality-enhancing process during the second period are also evident in the growth incidence curves shown in Figure 3. During the first period, almost all percentiles experienced an increase in real wages (except at the upper tail of distribution). However, its intensity was decreasing, mainly from the median on, creating an equalizing pattern, especially among all workers. On the contrary, during the second period, all percentiles suffered a loss in real terms but with more intensity in the lowest part of the wage distribution.

Figure 3: Growth incidence curves



Source: authors' elaboration based on EPH.

In brief, during almost one decade, between 2003 and 2012, Argentina experienced an equalizing earnings growth pattern hand in hand with high economic growth (except for 2009 and 2012). However, the economic and labour market situation changed dramatically since then. In a context of negative or slightly positive GDP growth rates, average earnings grew well below inflation and in an unequalizing manner.

Therefore, taking into account these opposing trends, the analysis for the entire period will be divided into two sub-periods: 2003–12 and 2012–19.

Next, we analyse the changes in employment composition to later discuss the evolution of real earnings; finally, we consider all these factors together to assess the role of changes in occupations and job task content in shaping the above-shown evolution of inequality.

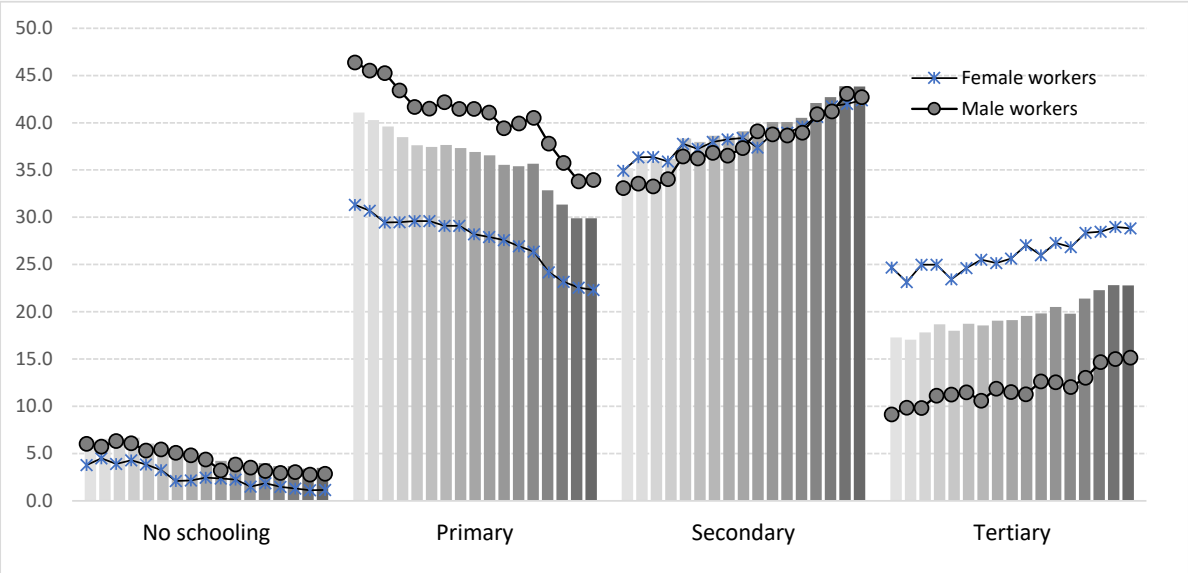
5 Changes in employment composition and the job polarization hypothesis

5.1 Employment growth by education level and type of occupation

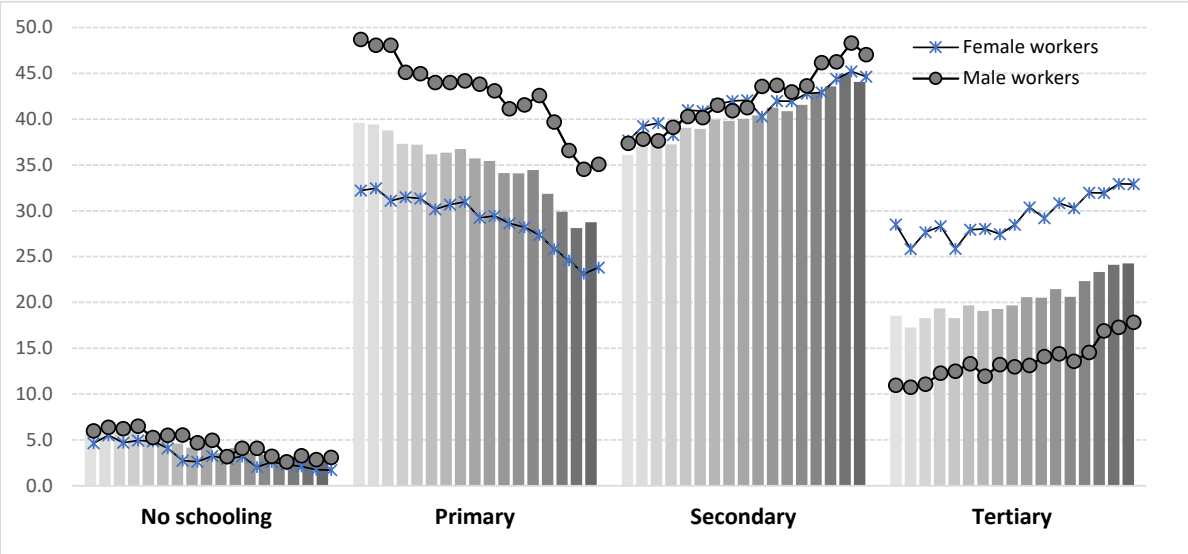
Despite the erratic Argentine macroeconomic and labour market performance, some long-term trends were observed during the almost 20 years under study. In particular, following a long-standing trend, the Argentine workforce became more skilled: there was an increase in the proportion of workers with secondary and university education (+14 pp) and a fall in workers with no schooling or primary education. This sustained education upgrading was verified among all workers and also among paid employees, both women and men (Figure 4).

Figure 4: Distribution of workers by education level

(a) All workers



(b) Paid employees



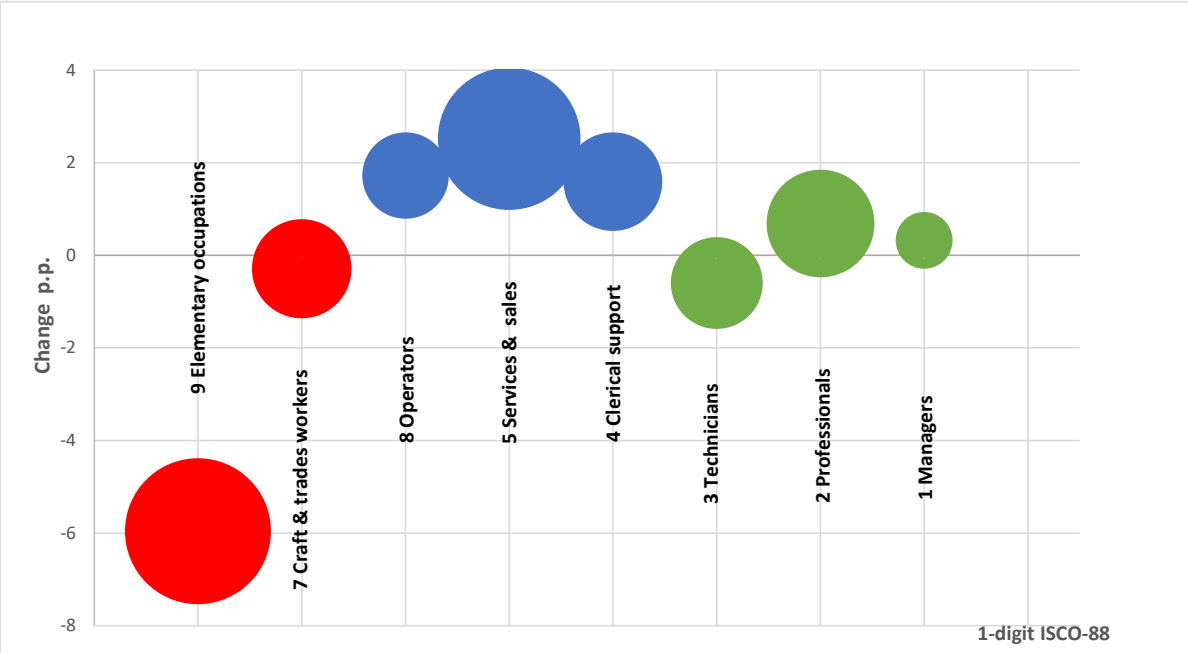
Source: authors' elaboration based on EPH.

In 2019, almost all workers had completed primary education (only 4 per cent had no education). However, for about 40 per cent of men and 26 per cent of women this was the only level of

schooling achieved in Argentina. At the other extreme, a third of women and about 20 per cent of men have a university degree.

Together with the education level of workers, another important dimension in this study is the composition of employment by type of occupation, and its changes over time. Considering ISCO-88, Figure 5 shows changes in the occupational share at the one-digit level ranked by the median years of education at the initial year, which at the same time coincides with the ranking by median earnings. To avoid any bias due to the fact that small jobs drive dominating results, each job is weighted by share of total employment.

Figure 5: Changes between 2003 and 2019 in occupation share (pp) (ISCO-88, one-digit)



Note: pp, percentage point. Bubble size indicates the initial relative importance of each occupation in total urban employment. Colour groups are organized as follows: red for low-skilled (low-paying) manual occupations, blue for middle-skilled (white and blue collar) occupations, and green for non-manual cognitive high-skilled jobs.

Source: authors' elaboration based on EPH.

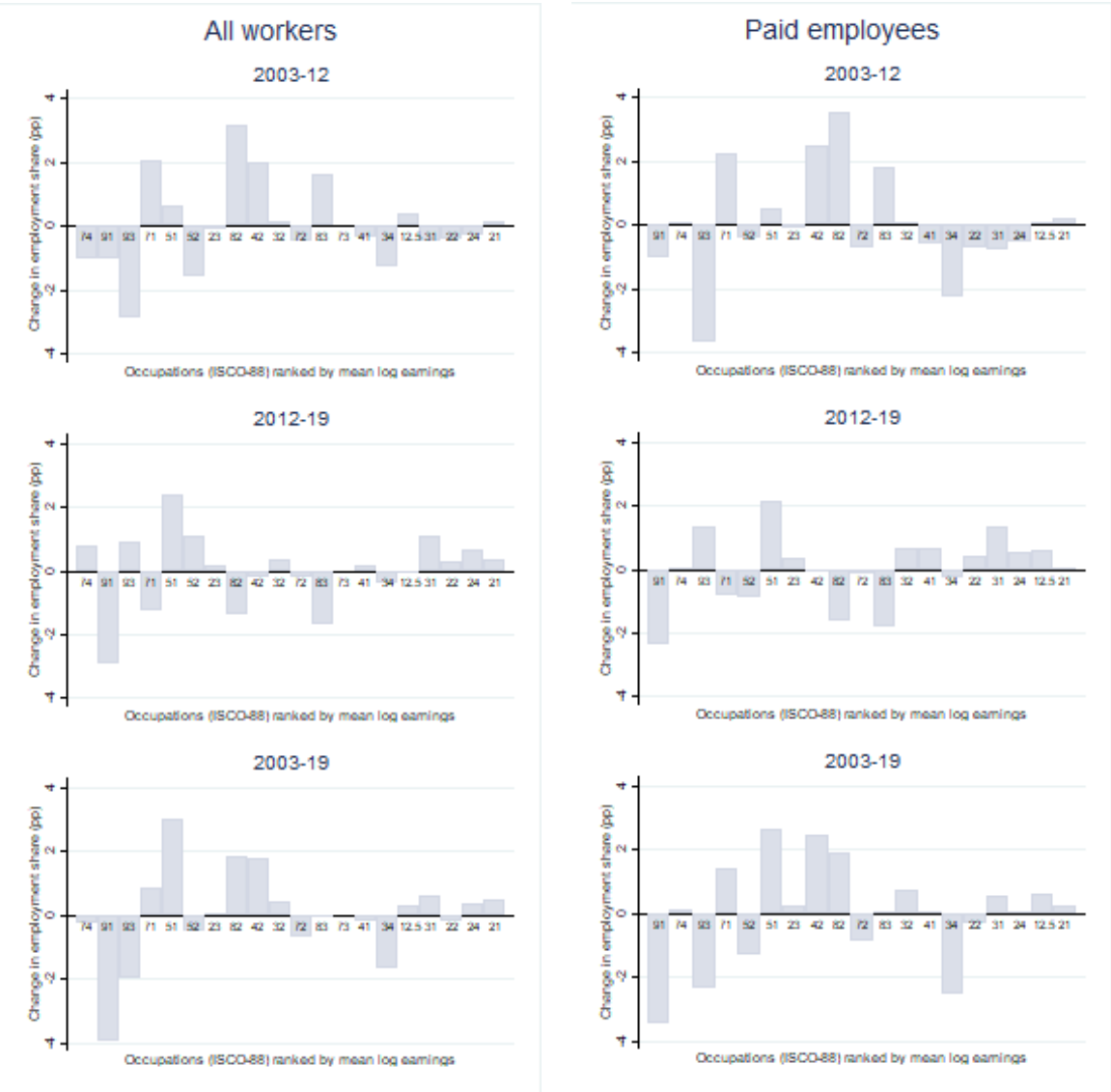
Elementary occupations—biggest share in total employment at the beginning of the period—experienced the greatest reduction over time (−6 pp), both for wage earners and for all workers. This was the most outstanding change in the occupation composition between 2003 and 2019. This fall meant that it stopped being the main source of employment to become the second at the end of the period. The increase in the proportion of the three important groups of occupations located in the centre of the ranking—clerks, sales and services workers, and machine operators—is also evident. Additionally, there is partial compensation among the highest-educated groups, with a drop in technicians and a rise in professionals.

In 2019, sales and services workers composed the biggest occupational groups among all workers, concentrating about one-quarter of all workers in 2019. They were followed, in importance, by elementary occupations, generating an additional 17 per cent of employment. Therefore, in 2019 these two groups concentrated about 42 per cent of the total workers, showing that a significant share of Argentine occupied people has occupations that require low- or middle-level skills. Managers represent the smallest group among the total urban employment (only about 4 per cent).

The increase in operators, assemblers, clerical, and sales and services workers compared with the reduction of elementary occupations over the 2000s clearly contrasts with the trends of high-income countries and, consequently, questions the appropriateness of the job polarization hypothesis in Argentina. On the contrary, the relocation from low- and—to a lesser extent—from high- to middle-skilled occupations seem to be more consistent with an inverted U-shaped profile.

However, this analysis must be complemented with an evaluation at a higher level of disaggregation of occupational groups. Figure 6 displays the percentage point change in the employment share as measured by ISCO-88 two-digit occupations and ranked by the initial log mean of weekly earnings for each job. From this, we can derive two important findings. First, the ranking is similar to that observed previously. In particular, those occupations included in groups 7 and 9 are mostly located at the bottom tail while those pertaining to groups 1, 2 or 3 are top-paid jobs. Second, the pattern of changes in the employment shares over time are also similar to those observed previously: worker relocation from low-paying to middle-paying jobs (with some exceptions). This is more evident in the case of paid employees. High-paying occupations exhibit a slight increase along the whole period.

Figure 6: Changes in employment share by occupation (ISCO-88, two-digits)



Source: authors' elaboration based on EPH.

These trends, however, were not homogeneous over the 2000s. During 2003–12, a shrinking in top-paid jobs was additional to the decline in the bottom-paid occupations, especially among employees. In particular, the two (low-skilled) elementary occupations (located at the bottom part of the distribution) lost relative importance between 2003 and 2012. Additionally, almost all groups of workers classified as managers, professionals, or technicians (located mostly at the top tail of distribution) also reduced their share in total employment or remained relatively unchanging. The joint consequence of these movements is an enlargement of the central part of the distribution. In particular, the categories of operators and clerks increased their relative importance.

These findings seem to be in line with those shown by Maloney and Molina (2016) for other Latin American countries, where they did not find a fall in operators and assemblers, but they did find a decline in elementary occupations and positive employment growth among high-skilled occupations.

In a context of low economic dynamism and increasing labour market difficulties, the trend for the period 2012–19 is less clear. Several occupation groups show an opposite tendency to that observed during the first period. In particular, most of the two-digit jobs pertaining to the three highest skilled occupations (managers, professionals, or technicians) saw a slight growth, while some middle-paying occupations diminished. At the other end of the earnings distribution, after the sharp fall in construction, manufacturing, and transport occupations (93) during the first sub-period, these workers partially recovered their share in total and salaried employment. However, sales and services elementary occupations—where half are domestic helpers and cleaners—records a continued decline, even more marked than that of the first period.

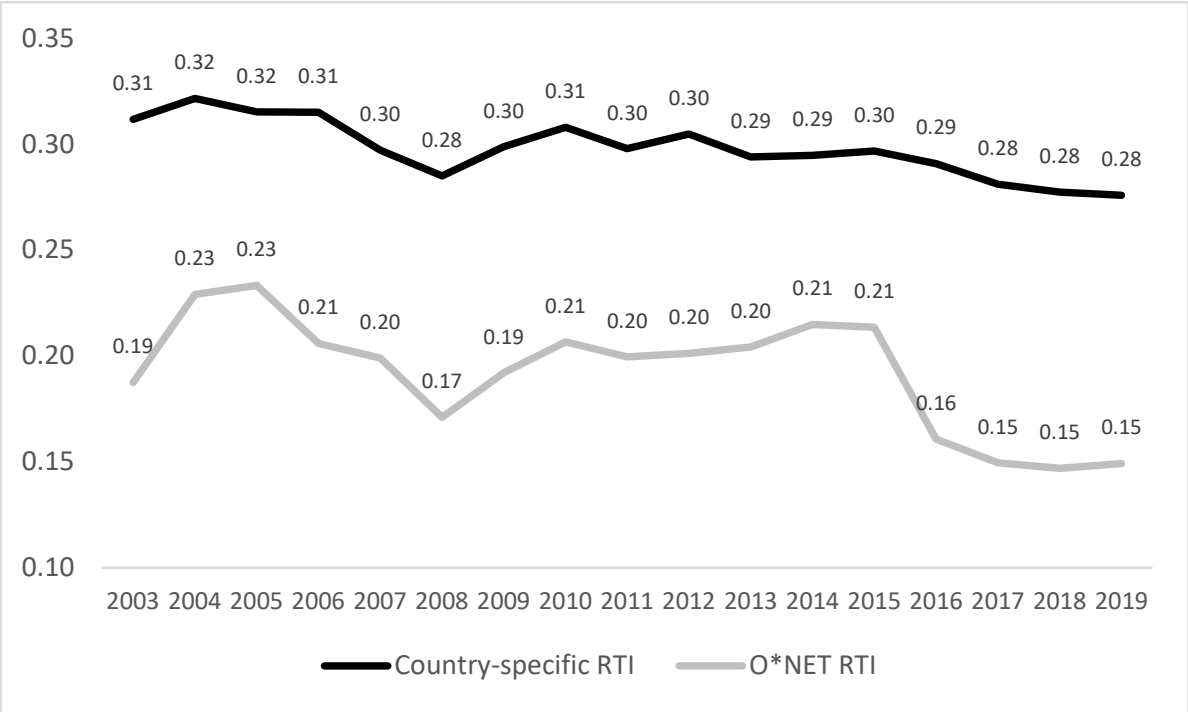
The overall result of all these changes is a slight growth in the share of non-routine cognitive occupations located at the upper end of the distribution and a sharp fall in elementary occupations, confirming the aforementioned conclusions for the one-digit analysis. Although the trend in both ends is clear, distribution in the middle is more heterogeneous and some of the occupations located in this part grew.

5.2 Employment composition by job task content

In addition to the analysis of the changes in occupations, another central aspect of this paper is the task-based analysis within occupations. As mentioned before, the analysis is mainly based on the CS-RTI index, but for sake of comparison we also present results using O*NET RTI. As shown in Figure 7, both RTI indices computed for all workers evidence a reduction over time, the former showing a clearer decreasing trend.

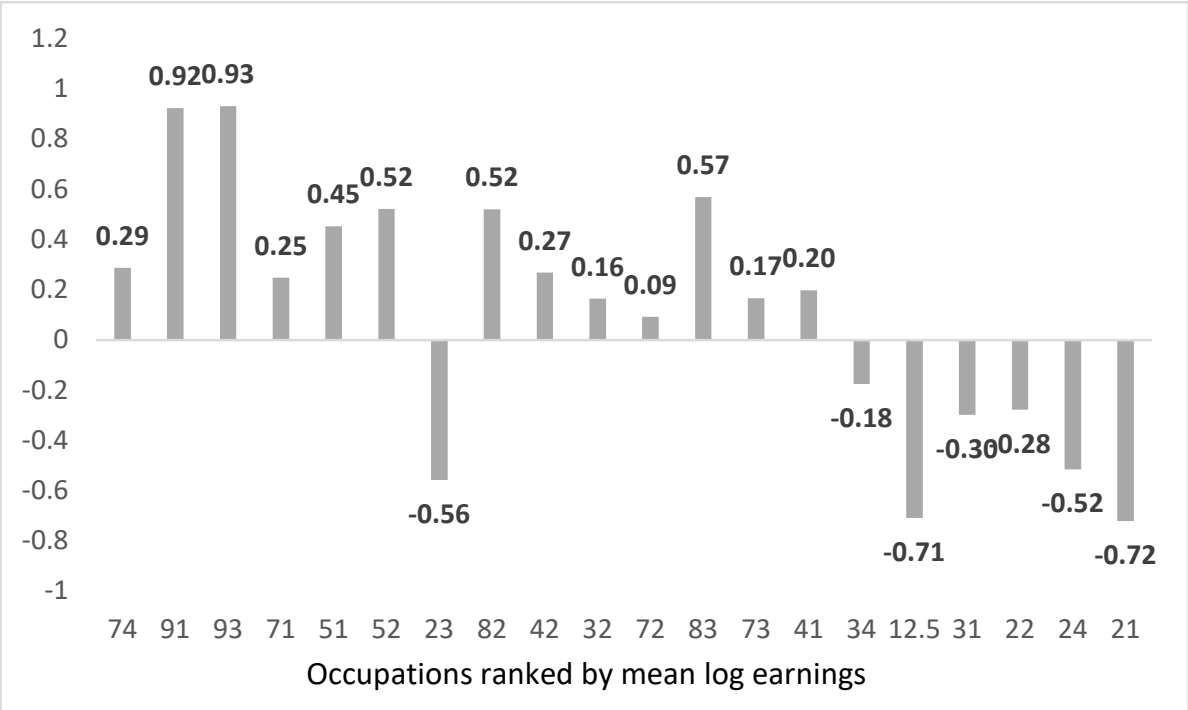
The reduction in the RTI index seems to be in line with the findings found for other countries. However, again, significant differences arise between Argentina and advanced countries. In particular, in Argentina the occupations with the highest routine task content (two-digit ISCO 91 and 93) are located at the lower end of the distribution, not in the middle. By contrast, those highly routine occupations in developed countries—such as office clerks (41) or handicraft and trade workers (73)—exhibit in Argentina an intermediate level of RTI. While personal and protective services (51) are low-paying jobs and have a low content of routine tasks in Europe (Goos et al. 2014), in Argentina they have a relatively high RTI. The correlation is higher among the high-paying occupations, all of them having low RTI (negative) and being in the upper tail of the distribution both in Argentina and in Europe (Figure 8).

Figure 7: Evolution of the aggregate routine-task intensity (RTI) indices



Source: authors' elaboration based on EPH.

Figure 8: CS-RTI by occupation (ISCO-88, two-digits)

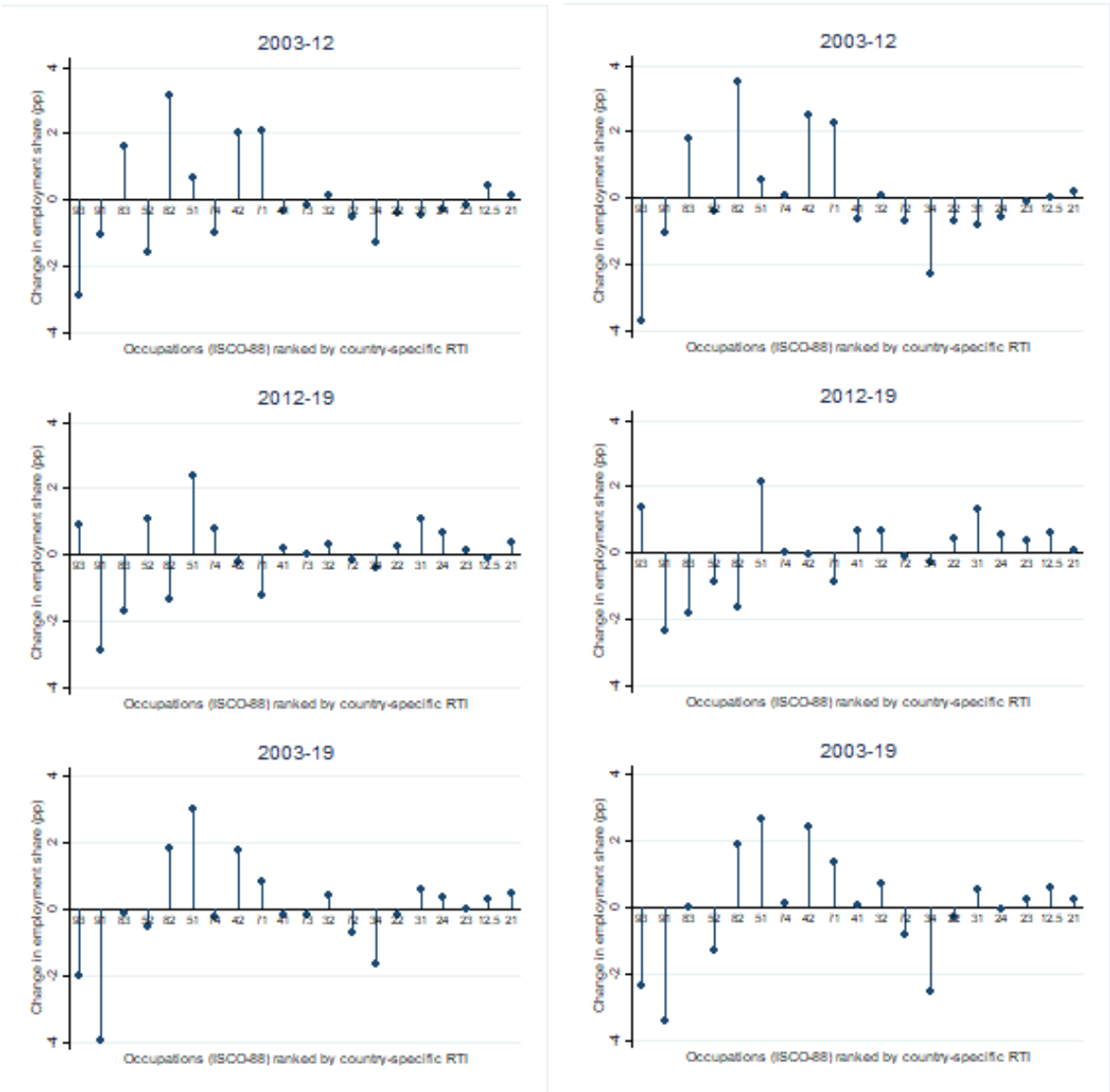


Source: authors' elaboration based on EPH.

Therefore, the reduction in the global RTI over the 2000s is mainly a consequence of the reduction in highly routine occupations (91, 93), also the lowest-paying, and the increase in non-routine and high-paying occupations.

Figure 9 shows the changes in employment share by ranking occupations according to CS-RTI instead of mean earnings. The patterns are again different for the two periods under analysis. During 2003–12, there was a reduction in the employment share at the lowest end of the distribution, showing a diminished share of occupations with high intensity of manual routine tasks, and a less marked drop (and a somewhat slight increase) among jobs placed at the other end of the distribution consequently enlarging the share of intermediate RTI occupations. During 2012–19, the contrast between the extremes is more evident: a decline in the relative importance of jobs located at the bottom tail of distribution and an increase of those occupation at the top.

Figure 9: Changes in employment share by country-specific RTI



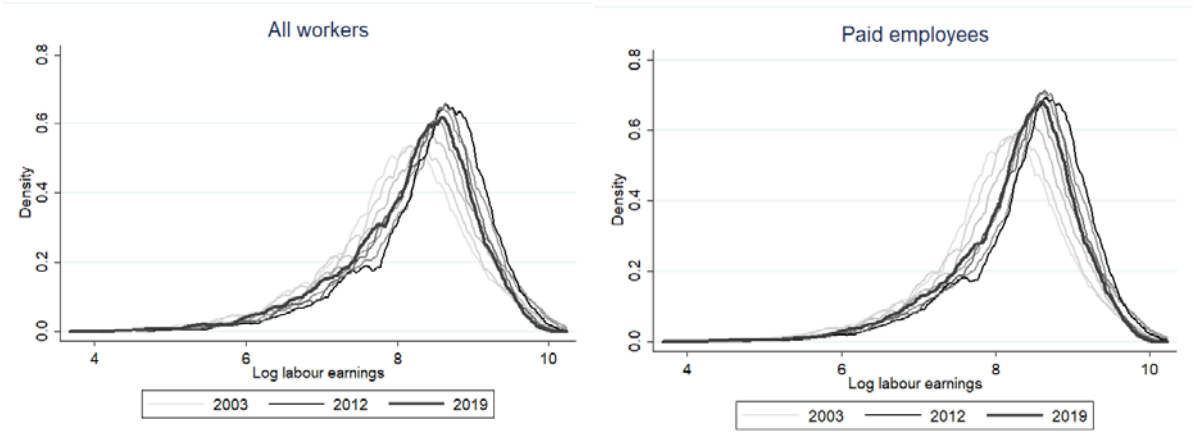
Source: authors' elaboration based on EPH.

6 The evolution of real earnings over time

In this section, we study the evolution of earnings in order to evaluate to what extent it matches with the dynamic of employment already analysed.

Similar to what has been pointed out regarding the evolution of employment during the new millennium, we can draw two marked cycles in average real earnings. In particular, an upward trend is observed for the period 2003–13 (with an increase of 50 per cent), followed by a strong decline from 2013 to 2019 (about 27 per cent). Indeed, the absolute kernel density curve shows a distribution shift to the right during the first period and a backward motion during the second phase (Figure 10). As mentioned earlier, the increasing macroeconomic difficulties, in general, and the acceleration of inflation, in particular, are responsible for this result. Between both ends of the period, however, there was a rise in average real earnings of around 10 per cent, both for paid employees and for all workers.

Figure 10: Absolute kernel density functions: real weekly earnings



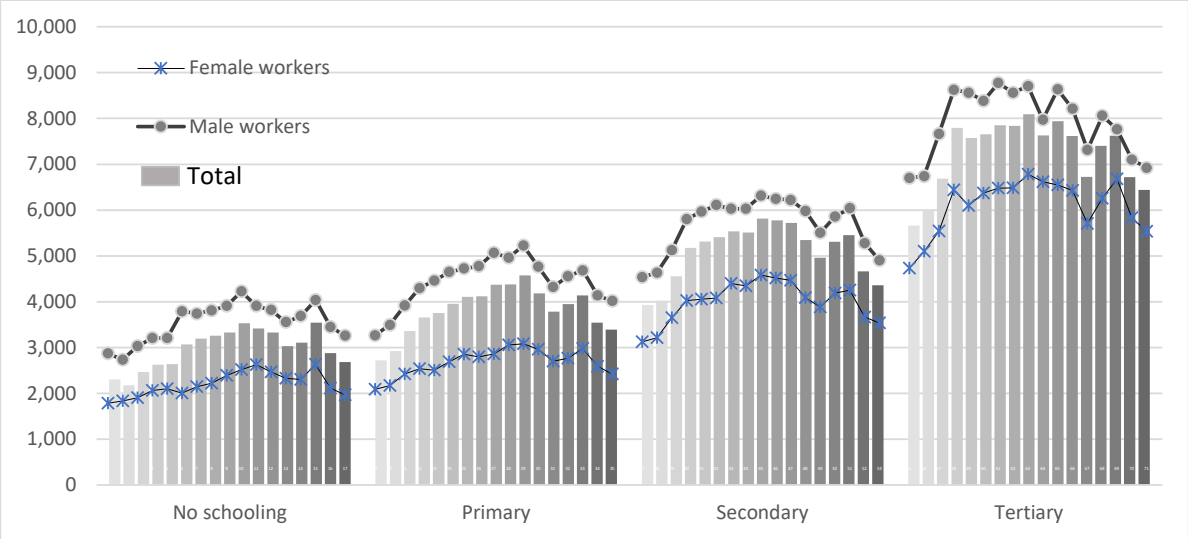
Source: authors' elaboration based on EPH.

Every education and gender group saw a wage rise along the whole period. However, those workers with the lowest skill level presented the greatest gains (Figure 11). In particular, the increase in real wages during the first phase was more intense among primary school workers. By contrast, the generalized fall in real earnings during the second period was stronger among medium-skilled workers (in particular, those with secondary schooling).

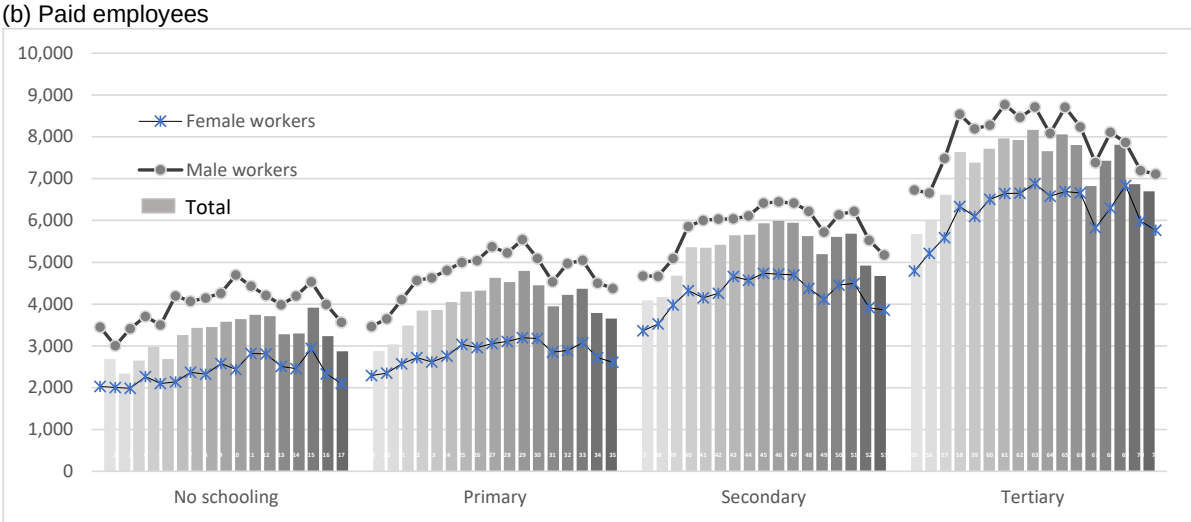
The two sub-periods also show highly contrasting wage behaviour across occupations (Figure 12). In particular, during 2003–12 the groups of jobs initially located in the first half of the distribution experienced a greater increase than those in the upper tail. However, there seems to be no linear trend between them, but rather an inverted U-shaped pattern. It is more evident for all workers than for specifically paid employees. As in the case of education and gender, during the second phase almost all occupations suffered a reduction in real earnings, being somewhat stronger for low-paying and middle-paying occupations. Over the 2000s, real earnings growth is registered across occupations but, consequently, lower than that of the first period.

Figure 11: Evolution of real weekly earnings by gender and education level

(a) All workers



(b) Paid employees

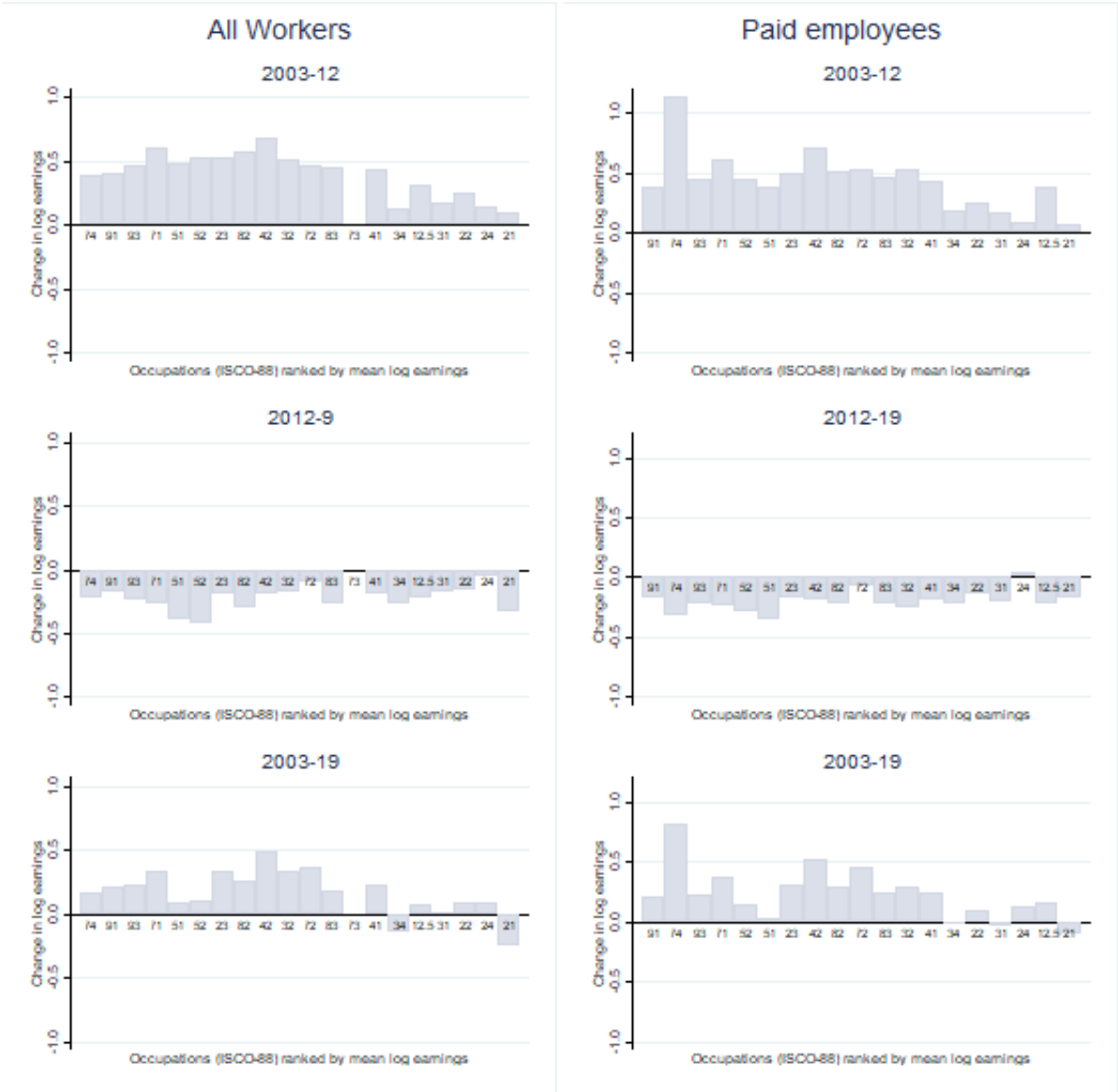


Source: authors' elaboration based on EPH.

Results of Mincer equations allow us to evaluate to what extent these trends in earnings by education level and type of occupation are also observed after controlling for other personal or job attributes. Table 2 shows the results. As expected, all coefficients of education dummies are statistically significant and positive ('non-schooling' being the baseline) and they stress the relevance of education in wage determination. There was a fall in the returns to schooling over time, which was systematic until 2012. Then, the premium to education exhibited fluctuations and finally an increase during the last years. As shown later, this behaviour is in line with the distributive dynamic observed in the country over time.

On the demand side, the type of occupation is also highly relevant. These results confirm that the returns for elementary occupations are lower than those for any other occupational group, while managers receive the highest. A fall is also observed in the premium to high-paying jobs until 2014 and this shows a contrasting behaviour in the latter years. Therefore, it is possible to conclude that both the level of education and the type of occupation are significant variables to explain not only wage gaps at a given time but also their variation throughout the 2000s.

Figure 12: Changes in earnings by occupation (ISCO-88, two-digits)



Source: authors' elaboration based on EPH.

Finally, another crucial dimension here is labour formality. As we can see in Table 2, formal workers receive an hourly wage significantly higher than informal workers. Even more so, the premium to formality widened over time. As mentioned above, different studies have shown that there has been a marked process of labour formalization in several countries in the region over the 2000s (ILO 2018; Amarante and Arim 2015; Maurizio 2015). According to the same studies, this process has been equalizing in some of those countries (ECLAC-ILO 2014; Beccaria et al. 2015).

Table 2: Mincer equations estimated by ordinary least square (OLS)

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Education: level no schooling																	
Primary	0.219***	0.177***	0.219***	0.229***	0.247***	0.182***	0.208***	0.189***	0.176***	0.175***	0.233***	0.163***	0.153***	0.224***	0.089**	0.160***	0.150***
	(0.060)	(0.044)	(0.037)	(0.038)	(0.043)	(0.044)	(0.044)	(0.052)	(0.045)	(0.044)	(0.048)	(0.042)	(0.044)	(0.054)	(0.045)	(0.057)	(0.050)
Secondary	0.416***	0.365***	0.385***	0.394***	0.428***	0.375***	0.374***	0.335***	0.316***	0.303***	0.338***	0.280***	0.269***	0.393***	0.235***	0.286***	0.253***
	(0.062)	(0.046)	(0.039)	(0.041)	(0.045)	(0.045)	(0.046)	(0.054)	(0.047)	(0.045)	(0.048)	(0.044)	(0.045)	(0.054)	(0.045)	(0.056)	(0.050)
Tertiary	0.596***	0.513***	0.569***	0.574***	0.579***	0.543***	0.527***	0.471***	0.475***	0.431***	0.485***	0.470***	0.404***	0.512***	0.359***	0.431***	0.378***
	(0.068)	(0.052)	(0.045)	(0.046)	(0.050)	(0.050)	(0.050)	(0.057)	(0.052)	(0.051)	(0.051)	(0.047)	(0.049)	(0.057)	(0.048)	(0.060)	(0.055)
Age: level 25–44 years																	
15–24 years	–0.369***	–0.288***	–0.310***	–0.316***	–0.316***	–0.279***	–0.282***	–0.265***	–0.278***	–0.284***	–0.249***	–0.252***	–0.226***	–0.212***	–0.334***	–0.253***	–0.296***
	(0.034)	(0.027)	(0.024)	(0.024)	(0.029)	(0.024)	(0.025)	(0.026)	(0.026)	(0.028)	(0.027)	(0.024)	(0.025)	(0.027)	(0.029)	(0.027)	(0.029)
45–64 years	0.068***	0.122***	0.080***	0.035**	0.031	0.036**	0.073***	0.046***	0.031*	0.037**	0.035**	0.054***	0.062***	0.048***	0.046***	0.075***	0.054***
	(0.023)	(0.020)	(0.018)	(0.017)	(0.019)	(0.018)	(0.018)	(0.018)	(0.017)	(0.018)	(0.017)	(0.016)	(0.016)	(0.017)	(0.017)	(0.017)	(0.017)
Female	–0.408***	–0.408***	–0.416***	–0.394***	–0.411***	–0.444***	–0.416***	–0.435***	–0.384***	–0.359***	–0.420***	–0.419***	–0.396***	–0.377***	–0.363***	–0.372***	–0.421***
	(0.023)	(0.020)	(0.018)	(0.017)	(0.019)	(0.017)	(0.020)	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)	(0.016)	(0.017)	(0.019)	(0.018)	(0.017)
Region: level Great Buenos Aires																	
Region=40	–0.434***	–0.366***	–0.370***	–0.358***	–0.327***	–0.379***	–0.344***	–0.344***	–0.303***	–0.236***	–0.283***	–0.234***	–0.238***	–0.210***	–0.212***	–0.170***	–0.193***
	(0.023)	(0.021)	(0.018)	(0.018)	(0.020)	(0.018)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.017)	(0.018)	(0.019)	(0.018)	(0.018)	(0.019)
Region=41	–0.421***	–0.380***	–0.397***	–0.355***	–0.284***	–0.271***	–0.248***	–0.278***	–0.300***	–0.262***	–0.261***	–0.210***	–0.220***	–0.199***	–0.187***	–0.191***	–0.168***
	(0.027)	(0.024)	(0.022)	(0.021)	(0.021)	(0.020)	(0.021)	(0.020)	(0.022)	(0.022)	(0.022)	(0.020)	(0.019)	(0.020)	(0.020)	(0.021)	(0.021)
Region=42	–0.332***	–0.239***	–0.253***	–0.265***	–0.137***	–0.172***	–0.152***	–0.246***	–0.186***	–0.135***	–0.126***	–0.153***	–0.099***	–0.153***	–0.138***	–0.072***	–0.110***
	(0.028)	(0.024)	(0.023)	(0.024)	(0.022)	(0.021)	(0.022)	(0.023)	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)	(0.021)	(0.022)	(0.023)	(0.022)
Region=43	–0.161***	–0.107***	–0.085***	–0.072***	–0.015	–0.067***	–0.061***	–0.082***	–0.050***	–0.085***	–0.037**	–0.041**	–0.042**	–0.022	–0.024	–0.012	–0.017
	(0.022)	(0.019)	(0.017)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.019)	(0.018)
Region=44	0.149***	0.193***	0.177***	0.301***	0.354***	0.310***	0.317***	0.271***	0.276***	0.269***	0.271***	0.305***	0.333***	0.331***	0.279***	0.280***	0.251***
	(0.028)	(0.025)	(0.024)	(0.023)	(0.020)	(0.020)	(0.019)	(0.021)	(0.022)	(0.022)	(0.022)	(0.021)	(0.020)	(0.019)	(0.021)	(0.021)	(0.022)
Migrant	0.126**	0.081**	–0.027	0.087**	0.008	–0.029	–0.038	–0.098**	–0.098**	0.045	0.057	–0.025	0.038	0.074**	–0.009	0.009	0.003
	(0.053)	(0.039)	(0.042)	(0.038)	(0.050)	(0.043)	(0.040)	(0.048)	(0.045)	(0.039)	(0.037)	(0.042)	(0.041)	(0.037)	(0.039)	(0.038)	(0.040)
Formal	0.599***	0.655***	0.648***	0.671***	0.631***	0.664***	0.708***	0.676***	0.655***	0.635***	0.639***	0.671***	0.685***	0.685***	0.648***	0.687***	0.715***
	(0.022)	(0.019)	(0.017)	(0.017)	(0.018)	(0.017)	(0.018)	(0.019)	(0.019)	(0.019)	(0.018)	(0.017)	(0.017)	(0.018)	(0.018)	(0.019)	(0.018)
ISCO-88 (1-digit) level 5 services and sales workers																	
ISCO-88 (1-digit)=1, 1 managers	0.686***	0.681***	0.719***	0.726***	0.815***	0.678***	0.659***	0.607***	0.598***	0.611***	0.568***	0.525***	0.628***	0.650***	0.581***	0.632***	0.626***
	(0.065)	(0.050)	(0.044)	(0.045)	(0.048)	(0.038)	(0.045)	(0.043)	(0.042)	(0.036)	(0.042)	(0.042)	(0.038)	(0.044)	(0.041)	(0.036)	(0.041)

ISCO-88 (1-digit)=2, 2 professionals	0.125***	0.197***	0.089**	0.142***	0.196***	0.150***	0.112***	0.142***	0.113***	0.035	0.112***	0.146***	0.117***	0.162***	0.158***	0.184***	0.206***
	(0.044)	(0.038)	(0.035)	(0.034)	(0.037)	(0.035)	(0.036)	(0.035)	(0.036)	(0.039)	(0.031)	(0.031)	(0.035)	(0.033)	(0.032)	(0.035)	(0.034)
ISCO-88 (1-digit)=3, 3 technicians and associate professionals	0.350***	0.326***	0.271***	0.280***	0.312***	0.271***	0.222***	0.227***	0.212***	0.185***	0.241***	0.194***	0.214***	0.271***	0.244***	0.231***	0.286***
	(0.038)	(0.032)	(0.033)	(0.031)	(0.034)	(0.031)	(0.032)	(0.033)	(0.032)	(0.036)	(0.030)	(0.028)	(0.032)	(0.029)	(0.029)	(0.030)	(0.030)
ISCO-88 (1-digit)=4, 4 clerical support workers	0.267***	0.258***	0.223***	0.246***	0.254***	0.225***	0.210***	0.184***	0.190***	0.180***	0.263***	0.266***	0.231***	0.249***	0.255***	0.305***	0.292***
	(0.034)	(0.027)	(0.025)	(0.025)	(0.027)	(0.025)	(0.027)	(0.026)	(0.026)	(0.025)	(0.024)	(0.024)	(0.021)	(0.024)	(0.023)	(0.024)	(0.023)
ISCO-88 (1-digit)=7, 7 craft and related trades workers	–0.054	0.098***	–0.006	0.048	0.053	0.069**	0.062*	0.041	–0.002	0.023	0.107***	0.108***	0.072**	0.101***	0.098**	0.139***	0.038
	(0.039)	(0.034)	(0.033)	(0.031)	(0.037)	(0.034)	(0.036)	(0.032)	(0.033)	(0.032)	(0.031)	(0.030)	(0.029)	(0.031)	(0.038)	(0.032)	(0.036)
ISCO-88 (1-digit)=8, 8 plant and machine operators and assemblers	0.223***	0.225***	0.169***	0.202***	0.197***	0.186***	0.156***	0.120***	0.175***	0.163***	0.196***	0.191***	0.144***	0.232***	0.191***	0.183***	0.180***
	(0.035)	(0.031)	(0.031)	(0.027)	(0.032)	(0.029)	(0.030)	(0.030)	(0.028)	(0.027)	(0.026)	(0.025)	(0.025)	(0.029)	(0.029)	(0.030)	(0.029)
ISCO-88 (1-digit)=9, 9 elementary occupations	–0.137***	–0.178***	–0.200***	–0.230***	–0.233***	–0.198***	–0.233***	–0.246***	–0.282***	–0.317***	–0.245***	–0.199***	–0.241***	–0.211***	–0.198***	–0.193***	–0.214***
	(0.032)	(0.029)	(0.026)	(0.026)	(0.031)	(0.026)	(0.029)	(0.030)	(0.028)	(0.027)	(0.029)	(0.026)	(0.025)	(0.027)	(0.027)	(0.029)	(0.026)
Constant	7.551***	7.562***	7.704***	7.760***	7.721***	7.835***	7.829***	7.922***	7.973***	8.002***	7.916***	7.872***	7.790***	7.715***	7.937***	7.664***	7.660***
	(0.066)	(0.050)	(0.044)	(0.045)	(0.051)	(0.051)	(0.050)	(0.061)	(0.053)	(0.049)	(0.056)	(0.050)	(0.049)	(0.060)	(0.051)	(0.063)	(0.056)
Observations	10,898	12,132	13,316	17,691	16,802	16,751	16,161	15,375	14,802	14,071	14,862	15,914	15,659	15,368	16,481	16,459	17,142
R-squared	0.418	0.459	0.456	0.487	0.471	0.484	0.475	0.481	0.480	0.454	0.458	0.461	0.447	0.457	0.424	0.435	0.441

Note: robust standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Source: authors' elaboration based on EPH.

7 The role of changes in occupations and job task content in shaping the evolution of earning inequality

The aim of this section is to evaluate the main drivers of the trends in earnings inequality in Argentina. For this, we first analyse the presence of polarization patterns in terms of either employment or earnings with respect to both initial earnings in a job and RTI. Then, we evaluate the role of the tasks performed by workers in their jobs in explaining inequality trends.

7.1 Job polarization

Descriptive results on employment composition changes previously analysed do not seem to be consistent with a polarizing profile; that is, middle-skilled jobs decreasing and high- and low-skilled occupations increasing. A quadratic model is used to evaluate, econometrically, the statistical significance of those trends (Goos and Manning 2007; Sebastian 2018). As mentioned, a polarization pattern involves a negative first (linear) coefficient followed by a positive quadratic coefficient. Table 3 summarizes the results.[5]

Table 3: OLS regressions for job polarization

	Log change in employment share					
	All workers			Paid employees		
Covariates	2003–12	2012–19	2003–19	2003–12	2012–19	2003–19
(Log) mean hourly wage (*t*–1)	5.360	2.313	5.483	5.386	–1.499	4.681
	(3.896)	(4.758)	(3.206)	(3.386)	(3.823)	(3.043)
Square (log) mean hourly wage (*t*–1)	–0.332	–0.134	–0.429***	–0.339	0.099	–0.284
	(0.243)	(0.285)	(0.049)	(0.214)	(0.231)	(0.194)
Constant	–21.625	–9.970	–22.460*	–21.395	5.587	–19.287
	(15.552)	(19.780)	(12.586)	(13.304)	(15.734)	(11.882)
Observations	20	20	20	19	19	19
R-squared	0.057	0.046	0.126	0.073	0.092	0.098
Adjusted *R*-squared	–0.054	–0.067	0.024	–0.0426	–0.0214	–0.0149
F-test	0.383	0.707	0.029	0.296	0.256	0.0384

Note: standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Source: authors' elaboration based on EPH.

As expected considering the previous analysis, we did not find a job polarization profile in Argentina over the 2000s. On the contrary, the sign of the coefficients for the whole period, and especially for the first sub-period, is consistent with an inverted U-shaped growth; however, the results were non-significant. This means that the relocation from bottom-paid and, to a lesser extent, from high-paid workers to middle-paid workers does not seem large enough to be reflected in the econometric results. In the second sub-period, the signs are even different among the total workers and employees. Only in the latter case they are consistent with a polarizing pattern. However, in neither group were the coefficients statistically significant.[6]

One crucial aspect when comparing these results for Argentina with those obtained for more developed countries is the ranking of occupations by earnings. Figure 13 is the replication of Figure

[5] It is important to remark that, given the availability of data in Argentina, we can run regression analyses at the two-digit level using only 20 observations. This limitation may partly explain the non-significant results.

[6] Appendix Figure A1 shows the correlation between initial (log) earnings and changes in employment by occupation.

6 with changes in the employment share, now ranked according to the average earnings recorded for European countries (Goos et al. 2014). The position of occupations along the distribution is different from that shown in Figure 6, however.

Figure 13: Changes in the employment share according to Europe's job ranking

Source: authors' elaboration based on EPH.

A particularly relevant example is group 51, 'personal and protective-service workers' (including personal care and related workers). Both in Argentina and in developed countries, this group of workers shows sustained relative growth over the period. However, while in Europe they are part of low-paying occupations (Goos et al. 2014) in Argentine they are middling to low-income workers, thus not part of the bottom tail of distribution. A similar situation is found in the case of group 52, 'salespersons'.

Another example is group 41, 'office clerks'. In Argentina, these workers are located in the upper half of the distribution while in Europe they are middling occupations, located lower on the earning ladder. The opposite occurs with group 74, 'crafts workers', since they are the lowest-paying occupations in Argentina but they are located in the middle of the distribution in European countries. Finally, group 32, 'life sciences professionals' are middling jobs in Argentina but high-paying occupations in European countries. Therefore, even if relative occupational change was similar, the global picture would still not be the same.

To further evaluate the patterns of changes in occupations, based on a task perspective, we perform again a quadratic regression—at the two-digit occupational level—of the log change in employment share on the level of routine intensity, using the CS-RTI measure. The results are shown in Table 4. The sign of the coefficients (first positive and then negative) for the whole period is consistent with this inverted U-shape; these changes, however, were again not strong

enough to throw statistically significant results. Therefore, the routine task content of occupations does not account for any definite pattern in employment changes at the occupational level.[7]

Table 4: OLS regressions for task composition polarization

	All workers			Paid employees		
	2003–12	2012–19	2003–19	2003–12	2012–19	2003–19
Country-specific RTI	0.026	–0.104	–0.044	0.181	–0.186*	0.012
	(0.097)	(0.076)	(0.083)	(0.142)	(0.094)	(0.113)
Country-specific RTI squared	–0.211	–0.085	–0.323*	–0.397	0.063	–0.315
	(0.221)	(0.166)	(0.161)	(0.262)	(0.166)	(0.193)
Constant	0.017	0.040	0.089	0.122	–0.065	0.070
	(0.088)	(0.067)	(0.088)	(0.109)	(0.067)	(0.112)
Observations	20	20	20	19	19	19
R-squared	0.032	0.116	0.164	0.300	0.233	0.126
Adjusted *R*-squared	–0.0816	0.0121	0.0651	0.212	0.137	0.0165
F-test	0.639	0.267	0.0510	0.0340	0.0490	0.212

Note: standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Source: authors' elaboration based on EPH.

7.2 Earnings polarization

We have shown that the type of occupation is a significant wage determinant and that job wage gaps have varied over time. We now go on to evaluate whether these changes are consistent, first, with a polarizing pattern, and, second, with the inequality trends observed over the period. For that, we fit the same quadratic model presented, but with the dependent variable being the change in the (log) mean earnings over time. The results are presented in Table 5.

Table 5: OLS regressions for earnings polarization

	Change in (log) mean wage					
	All workers			Paid employees		
	2003–12	2012–19	2003–19	2003–12	2012–19	2003–19
(Log) mean hourly wage (*t*–1)	6.703***	–5.773**	3.668**	5.489***	–3.603*	2.928*
	(0.765)	(2.263)	(1.675)	(1.043)	(1.752)	(1.604)
Square (log) mean hourly wage (*t*–1)	–0.429***	0.349**	–0.237**	–0.348***	0.217*	–0.188*
	(0.049)	(0.138)	(0.106)	(0.066)	(0.106)	(0.101)
Constant	–25.666***	23.553**	–13.941**	–21.145***	14.686*	–11.186*
	(2.962)	(9.265)	(6.574)	(4.092)	(7.187)	(6.349)
Observations	20	20	20	19	19	19
R-squared	0.750	0.362	0.314	0.611	0.284	0.217
Adjusted *R*-squared	0.721	0.287	0.234	0.562	0.194	0.119
F-test	0.000	0.036	0.043	0.000324	0.0704	0.0692

Note: standard errors in parentheses; ***p<0.01, **p<0.05, *p<0.1.

Source: authors' elaboration based on EPH.

Unlike what happens with employment, here all the coefficients are significant. For both groups of workers, an inverted U-shaped growth is found in the first period, showing that, in the sub-period characterized by a decreasing trend in inequality, real earnings growth was more intense in

[7] Similar regressions were made considering O*NET RTI measures. There was no single coefficient statistically significant. For reasons of space, they are not presented here but available upon request.

the middle part of the distribution. On the contrary, an earnings polarization pattern is found between 2012 and 2019. In the context of a generalized fall of real earnings and rising inequality, the greatest reductions were observed among middle-paid jobs. The results for the whole period reflect, although less strongly, what happened in the first sub-period.[8]

Two important points arise from these results. First, the international literature finds statistically significant changes either in occupations and earnings or only in occupations. As mentioned, for the United States, Autor and Dorn (2013) find that the changes in jobs followed the same pattern as those in earnings. In contrast, Goos and Manning (2007) for the United Kingdom and Sebastian (2018) for Spain account for job but not wage polarization. For Argentina, however, we find a third outcome: non-significant results in occupations but significant changes in earnings.

Second, earnings grew in low-paying occupations (elementary occupations) while, as mentioned before, employment shares fell for these jobs. This finding implies that forces other than labour demand and technology may also have had a great impact on recent wage dynamics and inequality in Argentina. In particular, as shown by Goos and Manning (2007), institutional factors can account for changes in earnings that do not match with changes in occupations. We will return to this aspect in the next section.

7.3 Earnings inequality across occupations and its relationship to routine task content

So far, we have shown that the type of occupation is a relevant factor in wage determination and that its influence has changed over time. Now, we evaluate whether changes in the return to occupations can explain the trend in earnings inequality. If so, this will be reflected in a wider earnings gap across occupations. On the contrary, if other factors mostly help to explain distribution patterns, this will be reflected in higher inequality within occupations in overall inequality trends.

To do this, we perform a Shapley decomposition that allows us to disaggregate the total Gini index into the contribution of inequality between and within occupations. Table 6 shows the results. Occupations at two-digit ISCO account for about one-third of overall earnings inequality.[9]

Table 6: Gini decomposition—the role of changes in occupation shares and wage gaps

	Actual			Shares constant			Means constant		
Gini	2003	2012	2019	2003	2012	2019	2003	2012	2019
1 Overall	0.466	0.368	0.389	0.466	0.378	0.396	0.466	0.398	0.412
2 Between-occupation	0.148	0.104	0.114	0.148	0.110	0.119	0.148	0.147	0.146
% 2/1	32	28	29	32	29	30	32	37	35
3 Within-occupation	0.318	0.265	0.275	0.318	0.265	0.275	0.318	0.250	0.266
% 3/1	68	72	71	68	70	69	68	63	65

Source: authors' elaboration based on EPH.

When evaluating the dynamic contribution of the two components to distribution changes we observed that the fall in inequality during the period 2003–12 was associated with both a decline

[8] Appendix Figure A1 shows the correlation between initial (log) earnings and changes in average earnings by occupation.

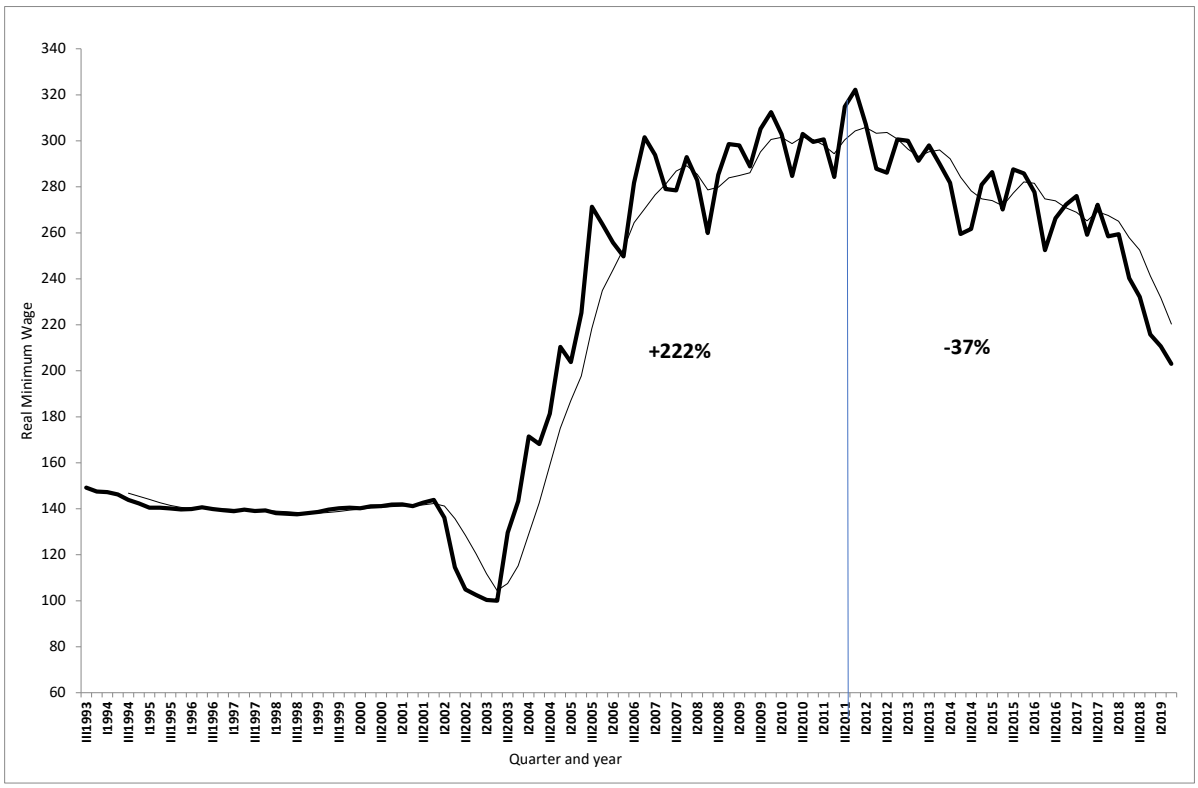
[9] This is higher than the contribution of occupation to inequality observed in some other countries. For instance, according to Gradín and Schotte (2020), occupation explained about 19 per cent of overall earnings inequality in Ghana in 2005–06 and it declined substantially thereafter, accounting for 11 per cent in 2016–17.

in the earnings gap between occupations, and a reduction in inequality within occupations. These two factors also explained the distributive worsening during 2012–19.

Over time, however, the part of the inequality explained by wage dispersion within occupations grew from 68 per cent to 71 per cent, meaning that the type of job became less relevant to explain earnings inequality.

Most of the reduction in between-occupation inequality was observed during the first sub-period when, among other factors, the strengthening of minimum wage played a highly important role. Over these years, this labour institution has entailed a material change compared with the systematic weakening it had suffered over the 1990s (Keifman and Maurizio 2012; Marinakis and Velasco 2006). Figure 14 allows to distinguish three different phases of the real minimum wage from the early 1990s to date. During the first phase, 1991–2001, both its nominal and real values remained stable at a low—non-binding—level. In 2003, after the sharp drop experienced as a consequence of the collapse of the currency board regime, a strong growing trend began that lasted until 2012. From that year on and linked to the acceleration of inflation, the purchasing power of this institution fell by approximately 40 per cent. Along this second sub-period the contribution of between-occupation inequality remains constant.

Figure 14: Evolution of the real minimum wage, 1993–19



Source: authors' elaboration based on EPH.

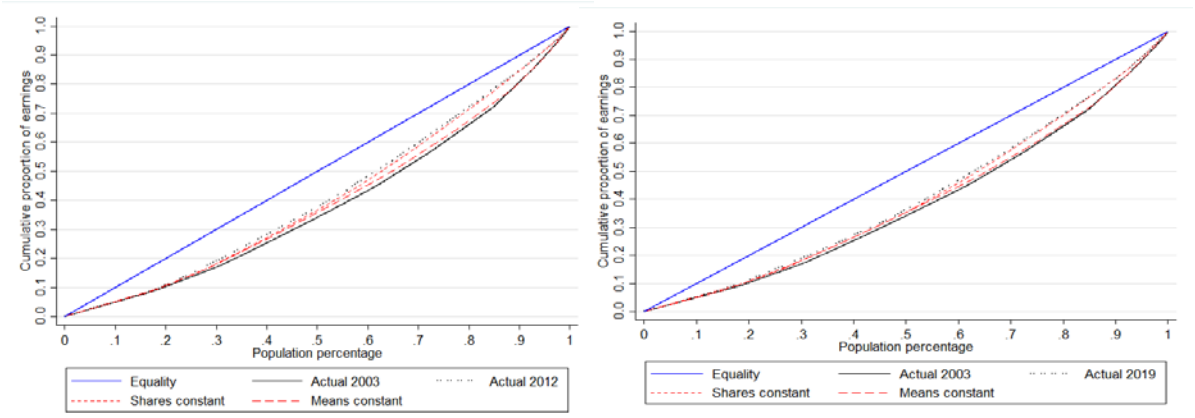
Another institutional force that could be associated with these results is the reinforcement of the collective bargaining. In particular, the number of sectoral collective agreements jumped from an annual average below 200 in 1991–2002 to more than 1,000 during the 2000s, and the number of private-sector workers covered increased 45 per cent between 1998 and 2008. In addition, as the ratio of collective-agreement wages to average wages also rose in the meantime, from 55 per cent in 2001 to 81 per cent in 2009, collective bargaining became more binding during these years (Keifman and Maurizio 2014). The coverage of this labour institution, in turn, increased with the formalization process that occurred mainly between 2003 and 2012. As in the case of minimum

wage, ceteris paribus, as this institution becomes more binding across jobs, the wage gap between occupations narrows. Therefore, the behaviour of this labour institution could have contributed to this result.

Table 6 also presents the same decomposition, but takes into consideration counterfactual distributions. In the first case, we assume an occupational share constant in order to evaluate the distributive impact of changes in average earnings across jobs ('Shares constant'). In the second case, we assume occupational earnings means constant to evaluate the contribution of changes in employment composition by occupation ('Means constant') to the evolution of inequality. This exercise allows us to better identify the role of changes in the composition of employment by occupation and the role of changes in mean earnings by occupation. Both factors followed the overall inequality trend over time, first equalizing and then inequality-enhancing.

The concentration curves presented in Figure 15 allow us to visualize the contribution of each factor to the changes in inequality. In particular, it is clear that the distributive improvements between 2003 and 2012 were associated with equalizing changes in the composition of employment and in average earnings. The second factor was significantly more important than the first. This scenario is repeated, less markedly, for the entire period.

Figure 15: Contribution of changes in employment and earnings to distribution



Source: authors' elaboration based on EPH.

Even more, the reduction in between-occupation inequality during the first sub-period was explained only by the fall in the gap of average earnings across occupations. On the contrary, without this equalizing pattern in average earnings, inequality between occupations would have increased as a result of changes in employment shares across occupations. Consequently, if the only changing variant had been the structure of employment by occupation, the contribution of within-occupation inequality would have fallen.

In addition, as a first step to directly evaluate the relevance of the degree of routinization to explain inequality between occupations, we compared the Gini between average earnings by occupation with the concentration index when occupations are sorted by RTI instead of by average earnings. The ratio between the concentration and the Gini index is a measure of the association between RTI and average earnings (based on the Gini metrics). Therefore, the value of this ratio is 100 per cent when there is perfect correlation between average earnings and RTI.

Table 7 presents the results. The correlation is high, about 80 per cent, indicating that the average earnings of occupations tend to increase with less routine-intensive jobs. Both the concentration index and (with less intensity) the ratio between concentration and Gini index between occupations

declined over time, indicating that RTI again became slightly less relevant to explain inequality across occupations. The ratio fell between 2003 and 2012 and increased between 2012 and 2019, ending up being similar between both ends of the period.

Table 7: Task composition and inequality between occupations

	Actual			Shares constant			Means constant		
Gini	2003	2012	2019	2003	2012	2019	2003	2012	2019
Gini between occupations	0.244	0.175	0.194	0.244	0.186	0.201	0.244	0.234	0.236
Concentration index	0.194	0.131	0.152	0.194	0.144	0.161	0.194	0.179	0.185
Ratio (%)	79	75	78	79	77	80	79	77	78

Source: authors' elaboration based on EPH.

7.4 Drivers of inequality trends—the RIF-regression decomposition

Finally, to further assess the role played by the routine task content of occupations in shaping inequality over time, we use a RIF-regression decomposition approach to estimate the relative importance of this factor controlling for other personal or job attributes.

Table 8 presents the results of the Gini coefficient decomposition for the whole period and for each sub-period. The first step of the decomposition shows that the changes in returns to the variables considered was the main driver of distributive shifts over time. In particular, the return effect explains 75 per cent or more of the Gini coefficient variation. The aggregate composition effect, however, also contributed to the fall in inequality during the first sub-period and over the whole of the period. Interestingly, the distributive worsening during the second phase is only explained by the unequalizing behaviour of the aggregate return effect.

Looking inside the composition effect, with the exception of age, changes in the demographic characteristics (sex, education, and ethnicity) do not seem to explain the trend in inequality. In accordance with our analysis, the formalization process has been one of the most relevant contributing factors to inequality decline, especially during the period 2003–12, when formality increased significantly.

However, we are here particularly interested in identifying the impact of changes in the employment composition according to the job task content on income distribution. In the United States, the consensus is that occupation polarization has contributed to a deepened economic inequality (Autor et al. 2006; Firpo et al. 2018). In Argentina, and as detailed earlier in our discussion, there was a movement from low-paying occupations—routine intense—to middle-paying occupations, especially during the period 2003–12 characterized by high job creation and decreasing unemployment and inequality. Consequently, we could expect most of these changes to reflect a transition of workers towards better paying occupations. If that was the case, occupational mobility patterns may have contributed to a better distribution over these years. In fact, as shown in Table 8, the shift of workers towards less routine-intensive occupations was equalizing, especially for paid employees.

Table 8: RIF-regression decomposition of Gini

	All workers						Paid employees					
	2003–12		2012–19		2003–19		2003–12		2012–19		2003–19	
	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
Distribution												
Final *F*	0.368	*0.004****	0.389	*0.003****	0.389	*0.003****	0.351	*0.004****	0.357	*0.003****	0.357	*0.003****
Initial *I*	0.465	*0.004****	0.368	*0.003****	0.465	*0.004****	0.431	*0.005****	0.351	*0.004****	0.431	*0.005****
Total change *F–I*	–0.097	*0.006****	0.021	*0.005****	–0.076	*0.005****	–0.079	*0.006****	0.006	*0.005*	–0.074	*0.006****
RIF aggregate decomposition												
RIF composition	–0.019	*0.002****	–0.001	*0.002*	–0.018	*0.003****	–0.020	*0.003****	–0.004	*0.002**	–0.022	*0.003****
RIF specification error	0.001	*0.001*	0.000	*0.001*	0.000	*0.001*	0.001	*0.001*	0.000	*0.001*	0.001	*0.001*
RIF earnings structure	–0.078	*0.005****	0.022	*0.004****	–0.057	*0.005****	–0.060	*0.006****	0.011	*0.004***	–0.052	*0.005****
RIF reweighting error	–0.001	*0.000**	0.000	*0.000*	0.000	*0.001*	–0.001	*0.000*	0.000	*0.000*	–0.001	*0.000*
RIF detailed decomposition												
RIF composition												
Age	–0.002	*0.001****	–0.001	*0.001*	–0.003	*0.001****	–0.001	*0.001***	–0.001	*0.001*	–0.002	*0.001***
Sex	0.000	*0.000*	0.001	*0.001***	0.001	*0.000**	0.000	*0.000*	0.001	*0.001*	0.000	*0.000*
Education	0.000	*0.001*	0.001	*0.001*	0.001	*0.002*	0.000	*0.001*	0.000	*0.001*	0.001	*0.002*
Ethnicity	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*	0.000	*0.000*
Region	0.002	*0.000****	0.001	*0.000****	0.002	*0.000****	0.001	*0.000****	0.001	*0.000****	0.002	*0.000****
Formality	–0.017	*0.002****	–0.001	*0.002*	–0.018	*0.002****	–0.015	*0.002****	–0.005	*0.002****	–0.020	*0.002****
CS-RTI	–0.002	*0.001***	–0.002	*0.001***	–0.002	*0.001**	–0.004	*0.001****	0.000	*0.001*	–0.003	*0.001***
Total explained	–0.019	*0.002****	–0.001	*0.002*	–0.018	*0.003****	–0.020	*0.003****	–0.004	*0.002**	–0.022	*0.003****
RIF earnings structure												
Age	–0.005	*0.005*	–0.002	*0.004*	–0.007	*0.004**	–0.005	*0.006*	–0.001	*0.004*	–0.005	*0.005*
Sex	0.018	*0.005****	0.002	*0.004*	0.018	*0.004****	0.025	*0.006****	0.002	*0.005*	0.025	*0.005****
Education	–0.003	*0.007*	0.001	*0.007*	0.001	*0.007*	–0.007	*0.007*	0.003	*0.007*	–0.002	*0.008*
Ethnicity	0.019	*0.026*	–0.011	*0.019*	–0.004	*0.025*	–0.001	*0.033*	–0.007	*0.023*	–0.013	*0.029*
Region	–0.009	*0.004***	–0.012	*0.004****	–0.020	*0.005****	–0.012	*0.005***	–0.004	*0.004*	–0.014	*0.004****
Formality	–0.015	*0.005****	0.012	*0.004****	0.000	*0.005*	–0.003	*0.005*	0.004	*0.004*	0.005	*0.004*
CS-RTI	0.021	*0.006****	–0.007	*0.005*	0.010	*0.005***	0.020	*0.006****	–0.003	*0.006*	0.014	*0.006***
Intercept	–0.102	*0.032****	0.040	*0.022**	–0.055	*0.028**	–0.077	*0.040**	0.016	*0.027*	–0.061	*0.032**
Total unexplained	–0.078	*0.005****	0.022	*0.004****	–0.057	*0.005****	–0.060	*0.006****	0.011	*0.004***	–0.052	*0.005****

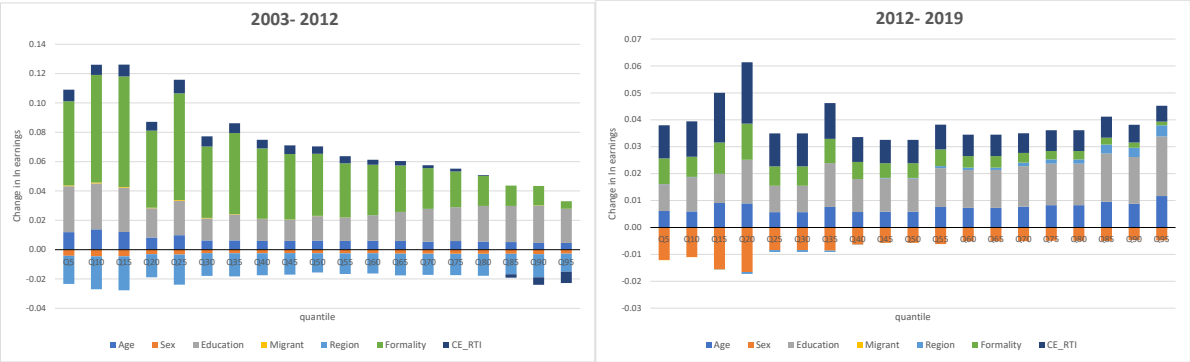
Note: RIF, recentred influence function; Coef. Coefficient; SE, standard error. Standard errors were estimated applying bootstrapping process with 200 replications; *p*-values were estimated assuming normal distribution; ***p<0.01, **p<0.05, *p<0.1.

Source: authors' elaboration based on EPH.

The Gini index reflects the aggregate impact on inequality. However, it is important to disentangle the impact of the different effects along the whole earnings distribution. For this, we use the RIF-regression decomposition technique to decompose changes over time by (log) quantiles. Appendix Tables A1 and A2 show the results of these estimations. Figure 16 displays the contribution of each variable to changes in quantiles across distribution.

The figure highlights the pro-poor profile associated with the increase in formality, in particular for the 2003–12 period. Occupational changes towards lower average levels of RTI during these years entailed a wage increase in the lowest quantiles, while the opposite effect is observed in the highest quantiles, thus rendering an equalizing effect. During the second period, the earnings increase associated with these changes was generalized but more intense in the lower end of the distribution.

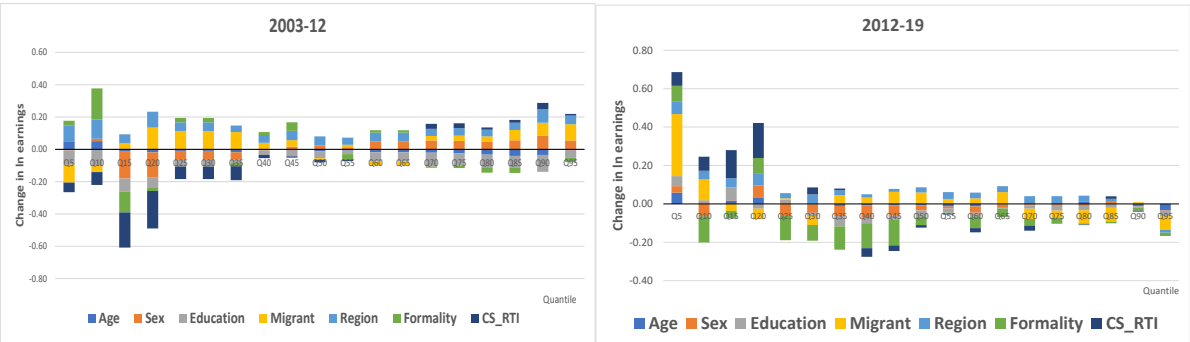
Figure 16: Detailed RIF decomposition—composition effect (all workers)



Source: authors' elaboration based on EPH.

Interestingly, the detailed decomposition of the earnings structure clearly shows a 'pro-rich' pattern of shifts in the returns to routine versus non-routine tasks in the first period, with a sort of upgrading effect (associated with an earnings reduction below the median and an increase above that). Although, during the second sub-period, returns to RTI seemingly had the opposite effect, particularly in the lower end of distribution, the net effect on Gini is not significant (Figure 17). Therefore, the net impact of this factor over the whole period was unequalizing (Table 8).

Figure 17: Detailed RIF decomposition—earning structure (all workers)



Source: authors' elaboration based on EPH.

8 Discussion

All results considered, we now deem relevant to discuss two aspects: first, the extent to which we should expect the trends in the composition of employment by occupation and its drivers in high-income countries to replicate in less developed countries; second, the distributive consequences of this process, which could also differ across countries.

In relation to the first, in this paper we assess the changes in the structure of employment by occupation and the content of tasks performed by workers in each of them in order to identify whether there has been a replacement of work in routine tasks in Argentina. These changes could be the result of an automation process but also of other domestic and external factors, the direct influence of which we are not evaluating.

With specific regard to technological change, Maloney and Molina (2016) state several reasons why we may not observe the same trends registered in the advanced world. In their view, the scope and speed of automation depends on the initial occupational composition (where, in some developing countries, there is a lower proportion of middle-income workers engaged in codifiable tasks), the technology absorptive capacity, the skill level of the workforce, and in some countries, the net result between being an offshoring destination and increased robotization.

To these arguments, we could add others for Argentina's particular case. This country registers the highest macroeconomic instability in the region (Rapetti 2019), which not only renders the process of adopting technology and automation slower but also can cause significant disruptions in the production structure, which in turn can lead to changes in employment composition. We have shown how the high real exchange rate during the first years after the collapse of the Convertibility Plan drove a growth in activity and employment levels in the tradable sectors, especially in the manufacturing industry. This, in part, explains the initial relative increase of one key job category—plant and machine operators and assemblers—, which was partially reverted when the industry job creation diminished, something that went hand in hand with a growing currency appreciation.

The contrasting changes in the job composition observed between the first and second sub-periods also open the question as to whether these are the reflection of strong macroeconomic fluctuations or rather a structural change that is closer to that in the advanced world, full realization of which calls for a longer period of time. Consequently, as they are ongoing processes, monitoring must continue.

As to the second aspect, the distributive impacts of the changing nature of work, in most advanced countries, the combination of routine-biased technological change and offshoring led to the displacement of middle-paid workers in routine occupations towards the extremes: less-educated workers moved towards bottom occupations, while higher-educated workers shifted towards highly paid non-routine occupations. These occupational changes are, in turn, the drivers of the earnings polarization and unequalizing changes. However, again, we would not necessarily expect to see the same pattern across the globe. Moreover, the absence of polarization does not imply that those processes do not hold.

Whether or not technological change and offshoring result in a polarizing pattern depends on several factors: (i) whether the jobs with the highest RTI are located at the bottom, middle, or top of the earnings distribution; (ii) the speed and type of technology adoption in the country; (iii) the position of the country in global value chains, in particular, whether it is a sender or receiver of offshored labour; and (iv) the existence of other domestic factors (e.g., labour institutions, education premium, formality).

As mentioned, Argentina's occupational ranking by skill, earnings, and task content does not fully coincide with that of developed countries. For example, unlike in developed countries, most routine occupations tend to be low paid in Argentina. So even similar movements in the employment share of each occupation can have a different overall impact on earnings distribution.

Moreover, the influence of labour institutions, such as the minimum wage or collective bargaining, which strengthened in Argentina especially during the period of a fall in inequality, can also account for wage rises, which do not necessarily respond to labour supply and demand forces nor to automation-related changes. The concomitant rise in average real earnings of low-paying occupations and its reduction in the employment share could be explained, at least partly, by the role played by these institutional rules.

9 Final remarks

This study has analysed the scope and characteristics of the structural transformation resulting from changes in the task content of jobs, and their impact on employment, earnings, and income distribution in Argentina during the new millennium. In this way, this paper contributes to the existing Argentine literature on occupational changes and inequality adding a novel dimension.

We observed the existence of a relocation from low-paying and, to a lesser extent, high-paying jobs to middle-paying jobs. This is not consistent with the job polarization pattern registered in some high-income countries. However, econometric results also reject the inverted U-shaped profile, implying that these changes were not strong enough—at least to date—to throw statistically significant results. On the contrary, in the case of earnings we found an inverted U-shaped growth in the first period. During the second period, however, an earnings polarizing pattern appeared in the context of a widespread fall in real earnings and weakening of labour institutions.

Therefore, like in some other countries, the trends in jobs did not follow the same patterns as the trends in earnings. However, unlike them, in Argentina we found a third outcome: non-significant changes in employment but significant changes in earnings. Even more, earnings grew in low-paying occupations while employment shares fell for these jobs. This finding implies that forces other than labour demand and technology may also have had a great impact on recent wage dynamics and inequality in Argentina.

The changes in the occupations towards lower average levels of RTI had, in turn, an equalizing effect, mostly in the first period, characterized by strong job creation and falling inequality. However, during the last years, this positive trend stagnated hand in hand with the weakening or reversion of other forces that also made the distributive improvements possible during the first years of the new millennium.

Overall, the results seem to suggest that macroeconomic conditions, the production structure, and domestic labour market institutions shape the impact of technology on job demand, on its composition, and on earnings distribution in a specific country. Thus, the policies that ease the transit across occupation and that protect the earnings of workers are especially relevant in a very unstable macroeconomic context where social protection mechanisms are scarce.

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Appendix A

A1 Assessment of the role of routine task content in shaping earnings inequality

To evaluate the impact of changes in the routine task content and other factors on earning distribution, we employed the Firpo et al. (2007, 2011) approach.

Let v be any functional of the conditional distribution of $F(Y|T)$, the total variation of v between T=0 and T=1 can be formalized as:

$$\Delta^v = v\left(F_{(Y_1|T=1)}\right) - v\left(F_{(Y_0|T=0)}\right)$$

where $F_{(Y_1|T=1)}$ is the earning distribution function in time 1, and $F_{(Y_0|T=0)}$ in time 0.

After the differences in the distribution of attributes between years is controlled by considering a counterfactual distribution $F_{(Y_0|T=1)}$—that is, the earning distribution that would have prevailed in $T=0$ if the individuals had the distribution of characteristics observed in T=1—it is possible to split up the total change into the 'composition effect' (Δ_C^v) and the 'earning structure effect' (Δ_S^v):

$$\Delta^v = \left[v\left(F_{(Y_0|T=1)}\right) - v\left(F_{(Y_0|T=0)}\right)\right] + \left[v\left(F_{(Y_1|T=1)}\right) - v\left(F_{(Y_0|T=1)}\right)\right]$$

$$\Delta^v = \Delta_C^v + \Delta_S^v$$

The composition effect measures the total change derived from modifications of the attributes while holding constant the earning structure between two moments in time. The second effect measures the impact of changes in returns, holding the structure of characteristics constant.

To conduct the first stage it is necessary to build on the contrafactual distribution; to that end, we follow the strategy based on a reweighting function given by the quotient between the distribution of X in T=1 and the distribution of X in T=0, both multivariate. Then, following DiNardo et al. (1996), and applying Bayes' rule, such quotient can be summarized as:

$$\psi(X) = \frac{Pr(T=1/X)}{Pr(T=0/X)}\frac{Pr(T=0)}{Pr(T=1)}$$

The $\hat{\psi}(X)$ generated by this procedure was used to reweight the observations registered in T=0 in order to estimate the counterfactual distribution of the functional of interest. On the other hand, the distributions associated with T=0 and T=1 were estimated straightforwardly by their respective empirical distributions. This is,

$$\hat{\Delta}^v = \left[v\left(\hat{F}_{(Y_0|T=1)}\right) - v\left(\hat{F}_{(Y_0|T=0)}\right)\right] + \left[v\left(\hat{F}_{(Y_1|T=1)}\right) - v\left(\hat{F}_{(Y_0|T=1)}\right)\right]$$

Finally, to obtain the detailed disaggregation of both effects (the second stage in the procedure), a recentred influence function (RIF) regression was applied to apportion the composition effect and the earning structure effect into the contribution of each individual covariable.

The RIF function is defined as $RIF(y;v) = v(F) + IF(y;v)$, where F is the distribution function of the variable of interest (in this case, wages) and IF is the influence function.

The composition and earning structure effects can be rewritten suitably in terms of expectation of the conditional RIF, considering the law of iterated expectations and the expected value of the influence function is equal to zero:

$$\Delta_C^v = E_X\left[E[(RIF(Y_0;v)|X,T=1)]\right] - E_X\left[E[(RIF(Y_0;v)|X,T=0)]\right]$$

$$\Delta_S^v = E_X\left[E[(RIF(Y_1;v)|X,T=1)]\right] - E_X\left[E[(RIF(Y_0;v)|X,T=1)]\right]$$

Letting $E[(RIF(Y;v)|X,T=t)] = X'\gamma_t^v$, and substituting the previous expressions by their respective linear projections, we obtain:

$$\Delta_C^v = E(X|T=1)'\gamma_{0I1}^v - E(X|T=0)'\gamma_0^v \equiv\equiv \sum_{k=1}^K (E(X^k|T=1)' - E(X^k|T=0)')\gamma_{0,k}^v + SPE^v \quad \text{(A1)}$$

$$\Delta_S^v = E(X|T=1)'\gamma_1^v - E(X|T=1)'\gamma_{0I1}^v \equiv\equiv \left(\gamma_{1,0}^v - \gamma_{0I1,0}^v\right) + \sum_{k=1}^K E(X^k|T=1)'.\left(\gamma_{1,k}^v - \gamma_{0I1,k}^v\right) + RWE^v \quad \text{(A2)}$$

where *k* refers to the *k*th attribute.

Equation (A1), 'the composition effect', is now expressed considering the specification error (SPE^v), originated in the fact that the procedure provides a first-order (linear) approximation of such effect. It can be estimated as the difference between the overall composition effect, obtained using the counterfactual distribution of wages, and the estimation of the effect obtained using RIF regressions. Equation A2 refers to 'the earning structure effect' and incorporates the error of reweighting (RWE^v), which results from the fact that the attributes of T=1 might not be exactly replicated when obtaining the counterfactual values.

The estimation procedure for the detailed decomposition of both effects is carried out by running a regression of the RIF of the functional of interest; that is, the ordinary least square method was chosen in this case.

Therefore, rewriting $v\left(\hat{F}_{(Y_1|T=1)}\right) = \hat{E}(X,T=1)\hat{\gamma}_1^v$, $v\left(\hat{F}_{(Y_0|T=0)}\right) = \hat{E}(X,T=0)\hat{\gamma}_0^v$, and $v\left(\hat{F}_{(Y_0|T=1)}\right) = \hat{E}(X,T=1)\hat{\gamma}_{0I1}^v$, we obtain the estimation of the detailed decomposition, given by:

$$\hat{\Delta}^v = \sum_{k=1}^K \left[\hat{E}(X^k|T=1) - \hat{E}(X^k|T=0)\right]\hat{\gamma}_{0,k}^v + \widehat{SPE}^v + \left(\hat{\gamma}_{1,0}^v - \hat{\gamma}_{0I1,0}^v\right) + \sum_{k=1}^K \hat{E}(X^k|T=1)'.\left(\hat{\gamma}_{1,k}^v - \hat{\gamma}_{0I1,k}^v\right) + \widehat{RWE}^v$$

Table A1: RIF-regression decomposition of the change in the relationship between earnings quantiles

All workers	2003–12									2012–19									2003–19								
	P50–P10			P90–P50			P90–P10			P50–P10			P90–P50			P90–P10			P50–P10			P90–P50			P90–P10		
	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*
Distribution																											
Final *F*	1.216	*0.057*	***	0.670	*0.053*	***	1.886	*0.045*	***	1.339	*0.028*	***	0.770	*0.019*	***	2.108	*0.032*	***	1.339	*0.028*	***	0.770	*0.018*	***	2.108	*0.032*	***
Initial *I*	1.288	*0.039*	***	0.972	*0.034*	***	2.260	*0.051*	***	1.216	*0.056*	***	0.670	*0.052*	***	1.886	*0.041*	***	1.288	*0.033*	***	0.972	*0.033*	***	2.260	*0.048*	***
Total change *F*–I	–0.072	*0.063*		–0.302	*0.064*	***	–0.374	*0.066*	***	0.123	*0.062*	**	0.100	*0.056*	*	0.222	*0.052*	***	0.051	*0.045*		–0.202	*0.036*	***	–0.152	*0.057*	***
RIF aggregate decomposition																											
RIF composition	–0.044	*0.013*	***	–0.035	*0.009*	***	–0.080	*0.016*	***	–0.002	*0.007*		0.007	*0.005*		0.005	*0.010*		–0.051	*0.020*	**	–0.014	*0.012*		–0.065	*0.022*	***
RIF specification error	0.029	*0.045*		–0.025	*0.022*		0.004	*0.046*		–0.070	*0.057*		0.102	*0.059*	*	0.032	*0.025*		–0.031	*0.022*		–0.032	*0.037*		–0.062	*0.043*	
RIF earnings structure	–0.055	*0.075*		–0.238	*0.059*	***	–0.293	*0.071*	***	0.195	*0.041*	***	–0.009	*0.033*		0.186	*0.035*	***	0.133	*0.043*	***	–0.155	*0.029*	***	–0.022	*0.047*	
RIF reweighting error	–0.003	*0.001*	*	–0.004	*0.001*		–0.006	*0.002*	***	0.000	*0.000*		0.000	*0.001*		0.000	*0.001*		0.000	*0.002*		–0.002	*0.001*		–0.002	*0.003*	
RIF detailed decomposition																											
RIF composition																											
Age	–0.008	*0.003*	**	–0.002	*0.002*		–0.009	*0.005*	**	0.000	*0.002*		0.003	*0.002*	*	0.003	*0.003*		–0.010	*0.006*		0.004	*0.004*		–0.005	*0.007*	
Sex	0.002	*0.003*		–0.001	*0.001*		0.001	*0.002*		0.005	*0.003*	*	0.001	*0.001*		0.006	*0.003*	**	0.008	*0.004*	*	–0.002	*0.002*		0.005	*0.004*	
Education	–0.015	*0.007*	**	0.009	*0.005*	*	–0.006	*0.007*		0.000	*0.004*		0.005	*0.003*		0.005	*0.005*		–0.026	*0.014*	*	0.023	*0.010*	**	–0.003	*0.016*	
Ethnicity	0.000	*0.002*		0.000	*0.001*		0.000	*0.002*		0.000	*0.002*		0.000	*0.000*		0.000	*0.002*		–0.001	*0.001*		0.000	*0.001*		–0.001	*0.002*	
Region	0.009	*0.004*	**	–0.003	*0.002*		0.007	*0.005*		0.000	*0.001*		0.003	*0.001*	***	0.003	*0.001*	***	0.011	*0.005*	**	–0.001	*0.003*		0.010	*0.006*	*
Formality	–0.031	*0.010*	***	–0.029	*0.006*	***	–0.060	*0.012*	***	–0.002	*0.002*		–0.004	*0.003*		–0.006	*0.005*		–0.036	*0.010*	***	–0.034	*0.007*	***	–0.070	*0.013*	***
CS-RTI	–0.002	*0.004*		–0.010	*0.005*	**	–0.012	*0.007*	*	–0.004	*0.003*	*	–0.002	*0.002*		–0.007	*0.004*	*	0.003	*0.006*		–0.004	*0.005*		–0.001	*0.009*	
Total explained	–0.044	*0.013*	***	–0.035	*0.009*		–0.080	*0.016*	***	–0.002	*0.007*		0.007	*0.005*		0.005	*0.010*		–0.051	*0.020*	**	–0.014	*0.012*		–0.065	*0.022*	***
RIF earnings structure																											
Age	–0.064	*0.034*	*	–0.021	*0.023*		–0.086	*0.038*	**	–0.009	*0.025*		–0.003	*0.020*		–0.012	*0.029*		–0.071	*0.030*	**	–0.020	*0.024*		–0.091	*0.037*	**
Sex	0.009	*0.053*		0.062	*0.024*	**	0.071	*0.060*		0.038	*0.036*		0.026	*0.022*		0.063	*0.039*		0.052	*0.042*		0.083	*0.030*	***	0.135	*0.048*	***
Education	0.061	*0.056*		–0.062	*0.043*		–0.001	*0.069*		–0.051	*0.049*		0.026	*0.028*		–0.024	*0.055*		0.023	*0.057*		–0.022	*0.042*		0.001	*0.067*	
Ethnicity	0.031	*0.174*		0.087	*0.117*		0.118	*0.198*		–0.050	*0.145*		–0.050	*0.087*		–0.099	*0.147*		–0.064	*0.157*		0.004	*0.124*		–0.060	*0.186*	
Region	–0.063	*0.035*	*	0.028	*0.023*		–0.035	*0.042*		–0.017	*0.028*		–0.030	*0.022*		–0.048	*0.033*		–0.069	*0.033*	**	0.003	*0.025*		–0.066	*0.038*	*
Formality	–0.195	*0.090*	**	0.000	*0.030*		–0.194	*0.091*	**	0.093	*0.045*	**	0.029	*0.025*		0.123	*0.043*	***	–0.087	*0.062*		0.064	*0.026*	**	–0.023	*0.065*	
CS-RTI	0.064	*0.057*		0.054	*0.026*	**	0.118	*0.061*	*	–0.086	*0.045*	*	0.008	*0.020*		–0.078	*0.049*		–0.013	*0.045*		0.039	*0.019*	**	0.027	*0.046*	
Intercept	0.102	*0.245*		–0.386	*0.151*	**	–0.284	*0.262*		0.277	*0.193*		–0.014	*0.109*		0.262	*0.189*		0.361	*0.214*	*	–0.306	*0.139*	**	0.055	*0.254*	
Total unexplained	–0.055	*0.075*		–0.238	*0.059*	***	–0.293	*0.071*	***	0.195	*0.041*	***	–0.009	*0.033*		0.186	*0.035*	***	0.133	*0.043*	***	–0.155	*0.029*	***	–0.022	*0.047*	

Paid employees	2003–12									2012–19									2003–19								
	P50–P10			P90–P50			P90–P10			P50–P10			P90–P50			P90–P10			P50–P10			P90–P50			P90–P10		
	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*	Coef.	SE	*p*
Distribution																											
Final *F*	1.171	*0.032*	***	0.682	*0.035*	***	1.853	*0.035*	***	1.215	*0.046*	***	0.707	*0.014*	***	1.922	*0.049*	***	1.215	*0.046*	***	0.707	*0.013*	***	1.922	*0.048*	***

Initial *I*	1.117	*0.027*	***	0.883	*0.035*	***	2.000	*0.041*	***	1.171	*0.030*	***	0.682	*0.034*	***	1.853	*0.032*	***	1.117	*0.028*	***	0.883	*0.037*	***	2.000	*0.045*	***
Total change *F–I*	0.054	*0.042*		–0.201	*0.052*	***	–0.147	*0.053*	***	0.044	*0.053*		0.025	*0.037*		0.069	*0.056*		0.098	*0.053*	*	–0.176	*0.038*	***	–0.078	*0.067*	
RIF aggregate decomposition																											
RIF composition	–0.033	*0.011*	***	–0.038	*0.009*	***	–0.071	*0.015*	***	–0.002	*0.008*		–0.002	*0.006*		–0.003	*0.012*		–0.044	*0.016*	***	–0.013	*0.012*		–0.057	*0.019*	***
RIF specification error	0.076	*0.042*	*	0.008	*0.017*		0.084	*0.045*	*	–0.011	*0.045*		0.007	*0.023*		–0.004	*0.042*		–0.071	*0.045*		0.003	*0.042*		–0.068	*0.056*	
RIF earnings structure	0.013	*0.056*		–0.168	*0.046*	***	–0.155	*0.061*	**	0.057	*0.056*		0.020	*0.019*		0.077	*0.060*		0.213	*0.070*	***	–0.164	*0.027*	***	0.049	*0.069*	
RIF reweighting error	–0.001	*0.002*		–0.004	*0.001*		–0.005	*0.003*	*	–0.001	*0.001*		–0.001	*0.001*		–0.001	*0.002*		–0.001	*0.002*		–0.002	*0.001*		–0.003	*0.003*	
RIF detailed decomposition																											
RIF composition																											
Age	–0.002	*0.002*		–0.001	*0.002*		–0.003	*0.003*		0.002	*0.003*		0.002	*0.002*		0.004	*0.004*		–0.001	*0.004*		0.005	*0.004*		0.004	*0.005*	
Sex	0.000	*0.002*		0.000	*0.001*		0.000	*0.001*		0.004	*0.004*		0.001	*0.001*		0.004	*0.004*		0.002	*0.002*		–0.001	*0.001*		0.000	*0.001*	
Education	–0.005	*0.005*		0.006	*0.005*		0.000	*0.007*		0.003	*0.005*		0.001	*0.004*		0.004	*0.006*		–0.009	*0.010*		0.018	*0.010*	*	0.009	*0.013*	
Ethnicity	0.000	*0.002*		0.000	*0.001*		0.000	*0.002*		0.000	*0.002*		0.000	*0.000*		0.000	*0.002*		–0.001	*0.002*		0.000	*0.001*		–0.001	*0.002*	
Region	0.006	*0.003*	**	–0.003	*0.002*		0.003	*0.003*		0.001	*0.001*		0.003	*0.001*	**	0.004	*0.001*	**	0.009	*0.004*	**	–0.002	*0.003*		0.007	*0.004*	*
Formality	–0.025	*0.007*	***	–0.021	*0.005*	***	–0.046	*0.009*	***	–0.007	*0.004*	**	–0.011	*0.004*	**	–0.018	*0.007*	**	–0.034	*0.008*	***	–0.029	*0.006*	***	–0.063	*0.010*	***
CS-RTI	–0.007	*0.004*	**	–0.018	*0.005*	***	–0.026	*0.007*	***	–0.004	*0.004*		0.003	*0.003*		0.000	*0.006*		–0.009	*0.004*	*	–0.005	*0.005*		–0.013	*0.007*	*
Total explained	–0.033	*0.011*	***	–0.038	*0.009*		–0.071	*0.015*	***	–0.002	*0.008*		–0.002	*0.006*		–0.003	*0.012*		–0.044	*0.016*	***	–0.013	*0.012*		–0.057	*0.019*	***
RIF earnings structure																											
Age	–0.029	*0.034*		–0.040	*0.027*		–0.069	*0.042*		0.007	*0.033*		0.012	*0.019*		0.019	*0.037*		–0.005	*0.033*		–0.026	*0.026*		–0.031	*0.040*	
Sex	0.039	*0.045*		0.060	*0.031*	*	0.099	*0.052*	*	0.066	*0.052*		0.004	*0.022*		0.070	*0.055*		0.168	*0.051*	***	0.064	*0.030*	**	0.232	*0.057*	***
Education	0.114	*0.062*	*	–0.096	*0.041*	**	0.018	*0.068*		–0.093	*0.070*		0.023	*0.032*		–0.070	*0.069*		–0.007	*0.062*		–0.054	*0.045*		–0.062	*0.070*	
Ethnicity	–0.167	*0.184*		0.003	*0.127*		–0.164	*0.229*		–0.179	*0.200*		–0.045	*0.092*		–0.224	*0.216*		–0.300	*0.176*	*	–0.046	*0.117*		–0.346	*0.209*	*
Region	–0.105	*0.041*	**	0.043	*0.025*	*	–0.062	*0.044*		0.004	*0.031*		–0.035	*0.020*	*	–0.031	*0.034*		–0.050	*0.036*		0.016	*0.025*		–0.034	*0.042*	
Formality	–0.222	*0.063*	***	0.030	*0.021*		–0.192	*0.063*	***	0.148	*0.069*	**	–0.018	*0.016*		0.131	*0.068*	*	0.059	*0.082*		0.012	*0.020*		0.071	*0.083*	
CS-RTI	0.017	*0.059*		0.058	*0.026*	**	0.076	*0.061*		–0.025	*0.062*		–0.006	*0.020*		–0.031	*0.063*		0.072	*0.071*		0.043	*0.027*		0.114	*0.073*	
Intercept	0.365	*0.247*		–0.225	*0.158*		0.139	*0.296*		0.129	*0.241*		0.086	*0.109*		0.214	*0.260*		0.277	*0.261*		–0.172	*0.144*		0.105	*0.293*	
Total unexplained	0.013	*0.056*		–0.168	*0.046*	***	–0.155	*0.061*	**	0.057	*0.056*		0.020	*0.019*		0.077	*0.060*		0.213	*0.070*	***	–0.164	*0.027*	***	0.049	*0.069*	

Note: Coef. Coefficient; SE, standard error; RIF, recentred influence function; CS-RTI, country-specific routine-task intensity. ***p<0.01, **p<0.05, *p<0.1. Standard errors were estimated applying bootstrapping process with 200 replications; p-values were estimated assuming normal distribution.

Source: authors' elaboration based on EPH.

Table A2: RIF-regression decomposition of the change in earnings quantiles

	2003–12																	
	Q10	*p*	Q20	*p*	Q30	*p*	Q40	*p*	Q50	*p*	Q60	*p*	Q70	*p*	Q80	*p*	Q90	*p*
Distribution																		
Final *F*	7.395	***	7.849	***	8.237	***	8.438	***	8.611	***	8.775	***	8.886	***	9.076	***	9.281	***
Initial *I*	6.798	***	7.407	***	7.727	***	7.900	***	8.086	***	8.231	***	8.446	***	8.720	***	9.058	***
Total change *F*–*I*	0.597	***	0.442	***	0.509	***	0.538	***	0.525	***	0.544	***	0.441	***	0.356	***	0.223	***
RIF aggregate decomposition																		
RIF composition	0.099	***	0.068	***	0.059	***	0.057	***	0.055	***	0.045	**	0.040	***	0.033	**	0.019	
RIF specification error	–0.001		–0.023		0.003		0.032	***	0.028	***	0.072		0.029	***	–0.086	***	0.004	
RIF earnings structure	0.496	***	0.395	***	0.447	***	0.448	***	0.442	***	0.427	***	0.372	***	0.411	***	0.203	***
RIF reweighting error	0.003		0.002		0.001		0.001		0.000		0.000		–0.001		–0.002	***	–0.003	***
RIF detailed decomposition																		
RIF composition																		
Age	0.014	**	0.008	*	0.006	*	0.006	*	0.006	**	0.006	*	0.005	*	0.006	**	0.005	*
Sex	–0.004		–0.003		–0.002		–0.002		–0.002		–0.002		–0.003		–0.003		–0.003	
Education	0.031	***	0.020	***	0.015	**	0.015	*	0.017	**	0.017	**	0.022	***	0.024	***	0.025	***
Ethnicity	0.001		0.000		0.000		0.000		0.000		0.000		0.000		0.000		0.000	
Region	–0.023	***	–0.016	***	–0.016	***	–0.015	***	–0.013	***	–0.014	***	–0.014	***	–0.015	***	–0.016	**
Formality	0.073	***	0.053	***	0.049	***	0.048	***	0.042	***	0.034	***	0.028	***	0.020	***	0.013	**
CS-RTI	0.007	***	0.006	***	0.007	***	0.006	***	0.005	**	0.003		0.002		0.001		–0.005	
Total explained	0.099	***	0.068	***	0.059	***	0.057	***	0.055	***	0.045	**	0.040	***	0.033	**	0.019	
RIF earnings structure																		
Age	0.051	**	–0.019	*	–0.009		–0.005		–0.013		–0.018		–0.020		–0.033		–0.035	**
Sex	0.015		–0.156	***	–0.050	**	–0.002		0.024	***	0.047	**	0.055	***	0.046	***	0.086	***
Education	–0.102	***	–0.064		–0.047		–0.028		–0.041	*	–0.056		–0.087	**	–0.078	***	–0.103	***
Ethnicity	–0.039		0.134	***	0.114	**	0.040		–0.008		–0.024		0.028	***	0.034	***	0.079	
Region	0.119	***	0.098	***	0.053	***	0.048	***	0.056	***	0.056	***	0.044	**	0.041		0.084	***
Formality	0.192	**	–0.018		0.027	***	0.019	*	–0.003		0.015	**	–0.007		–0.034	**	–0.002	
CS-RTI	–0.079		–0.232	***	–0.078	**	–0.020	***	–0.015	***	–0.001		0.031	***	0.013	***	0.038	***
Intercept	0.339	***	0.652	***	0.437	**	0.395	***	0.441	***	0.408	***	0.328	***	0.420	***	0.055	
Total unexplained	0.496	***	0.395	***	0.447	***	0.448	***	0.442	***	0.427	***	0.372	***	0.411	***	0.203	***
	2012–19																	
	Q10	*p*	Q20	*p*	Q30	*p*	Q40	*p*	Q50	*p*	Q60	*p*	Q70	*p*	Q80	*p*	Q90	*p*
Distribution																		
Final *F*	7.038	***	7.607	***	7.938	***	8.206	***	8.377	***	8.557	***	8.708	***	8.888	***	9.147	***

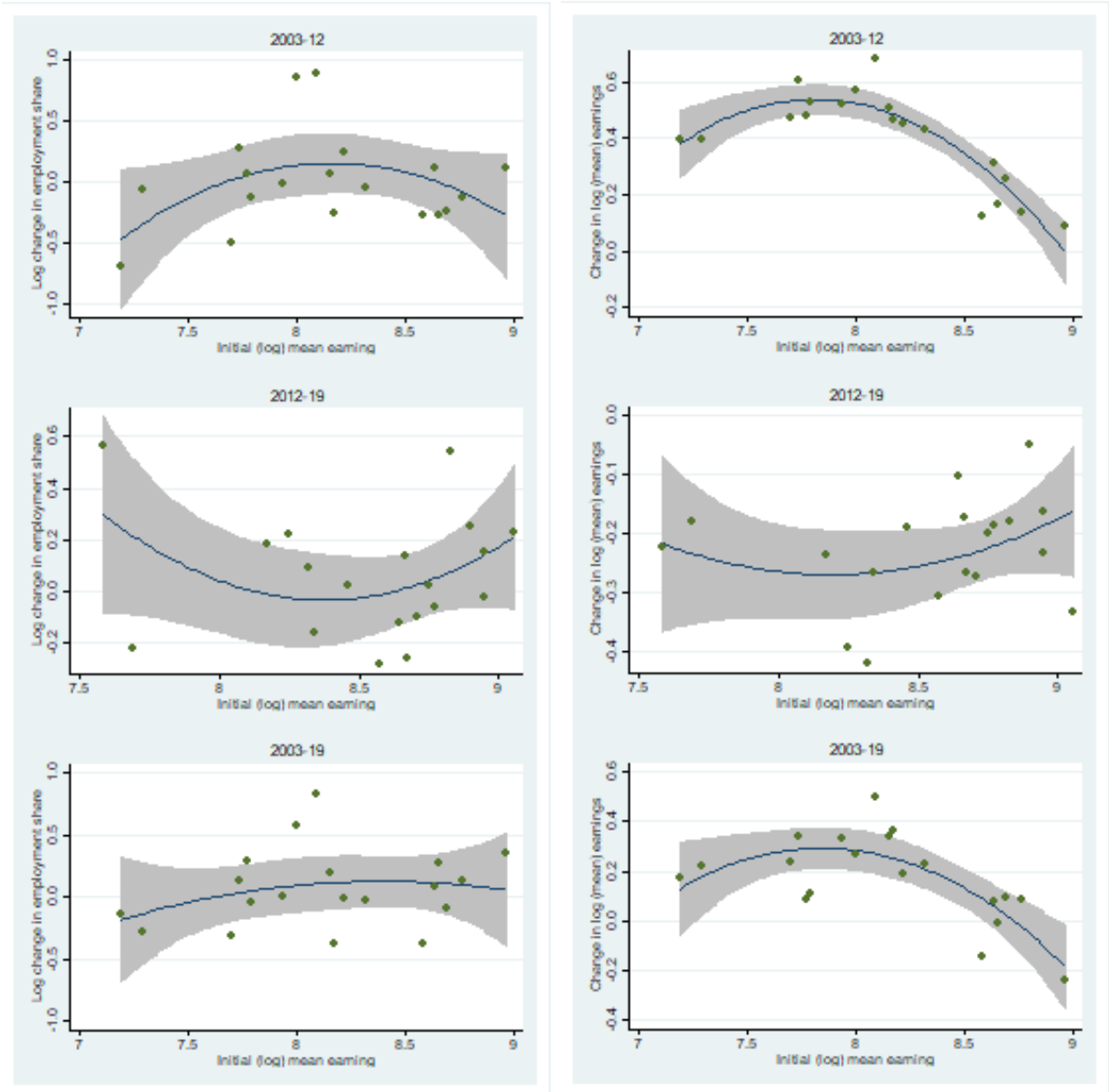
Initial *I*	7.395	***	7.849	***	8.237	***	8.438	***	8.611	***	8.775	***	8.886	***	9.076	***	9.281	***
Total change *F*–*I*	–0.357	***	–0.242	***	–0.299	***	–0.232	***	–0.234	***	–0.217	***	–0.179	***	–0.188	***	–0.134	**
RIF aggregate decomposition																		
RIF composition	0.028	***	0.044	**	0.026	**	0.027	**	0.027	**	0.029	***	0.030	***	0.031	***	0.033	***
RIF specification error	0.006	**	0.021		–0.047		0.024	***	–0.065		0.000		0.000		–0.001		0.037	
RIF earnings structure	–0.391	***	–0.308	***	–0.278	***	–0.284	***	–0.196	***	–0.246	***	–0.209	***	–0.219	***	–0.205	***
RIF reweighting error	0.000		0.001		0.001		0.000		0.000		0.000		0.000		0.000		0.000	
RIF detailed decomposition																		
RIF composition																		
Age	0.006	***	0.009	***	0.006	***	0.006	***	0.006	***	0.007	***	0.008	***	0.008	***	0.009	***
Sex	–0.011	**	–0.017	**	–0.008	**	–0.006	*	–0.006	**	–0.005	**	–0.005	**	–0.005	**	–0.005	*
Education	0.013	**	0.016	***	0.010	***	0.012	***	0.012	***	0.014	***	0.015	***	0.015	***	0.017	***
Ethnicity	0.000		0.000		0.000		0.000		0.000		0.000		0.000		0.000		0.000	
Region	0.000		–0.001	***	–0.001	**	0.000		0.000	**	0.001	**	0.001	**	0.002		0.003	*
Formality	0.007		0.013		0.007		0.006		0.005		0.004		0.004		0.003		0.002	
CS-RTI	0.013	*	0.023	**	0.012	**	0.009	*	0.009	*	0.008	**	0.007	**	0.008	***	0.007	***
Total explained	0.028	***	0.044	**	0.026	**	0.027	**	0.027	**	0.029	***	0.030	***	0.031	***	0.033	***
RIF earnings structure																		
Age	0.002		0.034		–0.002	**	–0.008		–0.007	**	–0.013		–0.002		0.011	**	–0.011	
Sex	–0.064		0.062	***	–0.044	***	–0.060	***	–0.027	***	–0.032	***	–0.007		–0.010		–0.001	
Education	0.017		–0.025	***	–0.017		–0.033	**	–0.033	***	–0.021	***	–0.017		–0.023		–0.007	
Ethnicity	0.109		–0.054		–0.046	***	0.033		0.059		0.029		–0.054	**	–0.068	***	0.009	
Region	0.045		0.061	**	0.049		0.017	*	0.028		0.030		0.040	***	0.032		–0.003	
Formality	–0.136	**	0.083	***	–0.082		–0.130	***	–0.043		–0.060	***	–0.034	**	–0.007		–0.014	
CS-RTI	0.073	***	0.183	***	0.036	***	–0.045	**	–0.013		–0.022	**	–0.026	***	–0.002		–0.005	
Intercept	–0.436	**	–0.650	***	–0.173	***	–0.058		–0.159		–0.157		–0.110		–0.151	*	–0.174	
Total unexplained	–0.391	***	–0.308	***	–0.278	***	–0.284	***	–0.196	***	–0.246	***	–0.209	***	–0.219	***	–0.205	***
	2003–19																	
	Q10		Q20		Q30		Q40		Q50		Q60		Q70		Q80		Q90	
Distribution																		
Final *F*	7.038	***	7.607	***	7.938	***	8.206	***	8.377	***	8.557	***	8.708	***	8.888	***	9.147	***
Initial *I*	6.798	***	7.407	***	7.727	***	7.900	***	8.086	***	8.231	***	8.446	***	8.720	***	9.058	***
Total change *F*–*I*	0.240	***	0.200	**	0.211	***	0.305	***	0.291	***	0.327	***	0.262	***	0.168	***	0.089	***
RIF aggregate decomposition																		
RIF composition	0.143	***	0.102	***	0.092	***	0.091	***	0.092	***	0.084	***	0.086	***	0.086	***	0.078	***
RIF specification error	0.060	**	–0.016		–0.088	**	0.035	**	0.029	**	0.076	**	0.030	***	–0.025	**	–0.003	

RIF earnings structure	0.039	***	0.117	***	0.209	***	0.181	***	0.173	***	0.169	**	0.149	***	0.110	***	0.017	
RIF reweighting error	–0.002		–0.003	*	–0.002	***	–0.002	***	–0.002	**	–0.002	**	–0.002	**	–0.003	***	–0.004	***
RIF detailed decomposition																		
RIF composition																		
Age	0.025	**	0.016	***	0.013	**	0.013	***	0.015	**	0.016	**	0.017	***	0.019	**	0.019	***
Sex	–0.017		–0.011		–0.009		–0.009	*	–0.009	*	–0.009	*	–0.010	*	–0.010		–0.011	
Education	0.061	***	0.040	***	0.031	***	0.031	***	0.035	***	0.038	***	0.050	***	0.054	***	0.058	***
Ethnicity	0.001		0.001	***	0.001		0.000		0.000		0.000		0.000		0.000		0.000	
Region	–0.026	***	–0.019	***	–0.018	**	–0.017	**	–0.015	**	–0.015	**	–0.015	**	–0.015	**	–0.015	**
Formality	0.086	***	0.061	***	0.057	***	0.056	***	0.050	***	0.040	***	0.032	**	0.024	**	0.016	**
CS-RTI	0.013	*	0.014	***	0.017	**	0.017	***	0.016	***	0.013	***	0.012	***	0.014	***	0.012	***
Total explained	0.143	***	0.102	***	0.092	***	0.091	***	0.092	***	0.084	***	0.086	***	0.086	***	0.078	***
RIF earnings structure																		
Age	0.050		0.014		–0.021		–0.011	**	–0.021	***	–0.039	**	–0.027	**	–0.035	**	–0.041	**
Sex	–0.059	***	–0.081	***	–0.125	***	–0.043	*	–0.007		0.021	***	0.053	***	0.053	***	0.076	***
Education	–0.092	***	–0.105	**	–0.066	***	–0.073	***	–0.069	**	–0.094	**	–0.117	**	–0.134	***	–0.091	***
Ethnic	0.114	***	0.154		0.076		0.091	***	0.050	***	–0.006		–0.059	***	–0.079	***	0.054	***
Region	0.145	***	0.127	***	0.069	**	0.073	***	0.076	***	0.088	***	0.086	***	0.082	***	0.079	**
Formality	0.007		0.054	***	–0.154	***	–0.073	***	–0.079	***	–0.045	**	–0.045	***	–0.047	***	–0.016	
CS-RTI	–0.002		–0.009		–0.088	***	–0.043	***	–0.015	**	–0.021	***	0.004		0.012		0.024	**
Intercept	–0.124		–0.037		0.518	***	0.260	***	0.237	***	0.265		0.254	***	0.257	***	–0.069	***
Total unexplained	0.039	***	0.117	***	0.209	***	0.181	***	0.173	***	0.169	**	0.149	***	0.110	***	0.017	

Note: ***p<0.01, **p<0.05, *p<0.1. Standard errors were estimated applying bootstrapping process with 200 replications; p-values were estimated assuming normal distribution.

Source: authors' elaboration based on EPH.

Figure A1: Correlation between initial (log) earnings and changes in average employment and earnings by occupation (all workers)



Source: authors' elaboration based on EPH.