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Jobs, earnings, and routine-task occupational change in times of revolution

The Tunisian perspective

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Abstract: In this paper we investigate the links between wage inequality and the changing nature of jobs in a revolution context. The methodology consists of various decompositions and regressions, including recentred influence function regressions, based on Tunisian labour force surveys from the past 20 years. Tunisia's labour market during the period of investigation is characterized by a decreasing earnings inequality following the fall of education premia, and an asymmetric wage polarization led by the increase of the lowest wages. After the Revolution, the routine task index increased significantly because of the rise of the share of routine agricultural and service workers. Although evidence shows that the routinization had a role in the evolution of the wage structure, it is not the main driver. Its effect was crowded out by employment and wage policies in the public sector.

Key words: routinization, wage inequality, tasks, Tunisia, recentred influence function regressions

JEL classification: C18, J21, J31

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1 Introduction

Tunisia is a lower middle-income country structurally characterized by high unemployment rates despite a sustained average growth rate from the mid-1990s to the global financial crisis of 5 per cent. In the last 20 years, youth unemployment has been severe, particularly for graduates.[1] Coupled with a widely shared sentiment of political discontent and rising cronyism among the population (Rijkers et al. 2017), the labour market outcomes fuelled the Revolution of 2011, with a long-lasting impact for the whole Middle East and North Africa (MENA) region. Tunisia and MENA are, however, not exceptions. In many places in the world, the combination of a youth bulge and low demand for skills have induced unemployment, overeducation, frustration, and rebellion (Nordås and Davenport 2013; Urdal 2006).

Our objective in this study is to analyse the dynamics of the jobs and earnings distributions in the decades preceding and following the Revolution and their determinants with a focus on the evolution of the nature of jobs according to their task content. Our aim is to identify regularities explained by structural factors such as demography, education, or computerization, and changes that may have occurred due to the Tunisian Revolution.

Much of the academic literature on employment and wage distribution focuses on levels of education, suggesting that the increasing gap between two distinct skill groups is the strongest determinant of earnings inequality. However, an influential and growing literature (Acemoglu and Autor 2011; Autor and Dorn 2013; Autor et al. 2003) has shown that a significant share of inequality in developed countries is also explained by inequality within skill groups, namely due to occupational change and the tasks associated with occupations. This literature highlighted the role of the evolution of occupations and tasks over time as a key determinant in understanding jobs and wage polarization (Autor and Dorn 2013). According to studies that use US task databases—the Dictionary of Occupational Titles (DOT) (Autor et al. 2003) and its successor, the Occupational Information Network (O*NET) (Acemoglu and Autor 2011)—routine tasks are mainly concentrated in average-wage occupations, while low-wage and high-wage occupations are characterized respectively by high intensity of manual and cognitive tasks. While this work was ground-breaking, it remains biased towards the task-based structure of occupations in the most developed countries. Indeed, as shown by Lewandowski et al. (2020), occupations in developing countries are more intensive in routine tasks than similar occupations in developed countries.

Studying the case of Portugal, a country with slow adoption of automation, Fonseca et al. (2018) show that the decline of routine manual task jobs is the main determinant of job and wage polarization, while routine cognitive task jobs do not witness a similar outcome. Lewandowski et al. (2019) test the routinization hypothesis in a broader context, including in developing countries, using survey-based and regression corrected estimations of routine-task intensity (RTI) in occupations on a country basis. Using global census data, Maloney and Molina (2019) also investigate polarization and automation links in developing countries, including the impact of developed countries' automation and offshore strategies on polarization in developing countries. Using Chinese data, Fleisher et al. (2018) highlight a redistribution of jobs from middle-income skills to low-income categories, but they do not find any evidence of polarization at the upper end of the skill spectrum, despite the development of routine tasks.

Bárány and Siegel (2018) propose a structural change-driven explanation of job polarization. One of their main arguments is that polarization started in the 1950s in the USA, long before the information and communication technologies (ICT) revolution. Their analysis is based on the complementarity between consumption goods in manufacturing (intensive in medium-skilled workers) and low-skill and high-skill services, and the increase of relative labour productivity in manufacturing, which pushes labour in the

[1] Between 30 and 40 per cent according to Asik et al. (2020).

two other sectors. This is in line with the work of Kupets (2016), who shows that job polarization in Ukraine is due to a structural change biased towards subsistence agriculture and low value-added services, rather than routine-based technological change.

Our first objective in this paper is to characterize the evolution of employment and earnings distributions and test for the polarization hypothesis before and after the Revolution. We then dig deeper into distributional changes across occupations by moving to the fine-grained analysis based on occupations and their task compositions. A Shapley decomposition allows us to decompose inequality into between- and within-occupations inequality. A recentred influence function (RIF) decomposition is performed to decompose the change in earnings in wage structure and composition effects and to assess the role played by various determinants of inequality. This allows us to check the Tunisian results against previous work and to focus on the specificity of the Tunisian context, including changes that occurred after the 2011 Revolution. Our ultimate goal is to disentangle the factors that explain earnings' inequality and any potential polarization observed. Highlighting the role of the Revolution mainly through its impact on public policy is one of the key objectives of the paper. This would allow us to humbly contribute to the debate on the economic impact of revolutions, often focusing on the French Revolution (Acemoglu et al. 2011; Finley et al. 2020).

The main result is that earnings inequality decreases significantly during the period of investigation in Tunisia due mainly to decreasing education premia. This is in line with Autor (2014), who considers that the evolution of education premia is the main determinant of wage inequality. The second result is that Tunisia had witnessed a shift towards jobs demanding high skills until the Revolution, then the movement was reversed. Moreover, wage polarization is highlighted, but unlike in developed countries, Tunisian polarization seems to have been mainly led by the increase of the lowest wages, similar to the phenomenon observed in China by Fleisher et al. (2018). We also find that half of the earnings inequality can be attributed to the between-occupations differences, most of which are explained by the task nature of the job. Finally, occupations, employment, and wage policies in the public sector and education account for most of the differential changes at the bottom and top of the distribution.

2 Data

2.1 Measures of routine-task intensity

Our first task-content measure was proposed by Autor et al. (2003), based on the US Department of Labor's DOT, and then its successor, O*NET. Autor et al.'s index (2003) was aggregated from five sub-indices measuring the intensity of five different types of task: non-routine cognitive, non-routine interactive, non-routine manual, routine cognitive, and routine manual. The O*NET RTI has been widely used in studying the relationship between technological changes and employment in developed countries (see Acemoglu and Autor 2011; Autor et al. 2008; Foote and Ryan 2015; Goos and Manning 2007; Graetz and Michaels 2017; Jaimovich and Siu 2012). For our usage, the O*NET-SOC occupations were mapped into the four-digit ISCO-88 occupations.[2]

The use of O*NET to quantify the RTI in developing countries, however, is contentious due to large differences in technological progress, globalization, structural change, and skill supply (Lewandowski et al. 2019). This requires us to look for another measure that takes into account these country-specific factors. Such a measure has been recently developed by Lewandowski et al. (2019) based on Autor et al.'s method (2003), but using job-task information collected from individual-level surveys in 41 countries around the world: the OECD's Programme for the International Assessment of Adult Competencies

[2] ISCO, International Standard Classification of Occupations.

(PIAAC), the World Bank's Skills Toward Employment and Productivity (STEP) surveys, and the China Urban Labor Survey (CULS). As a result, it does not only enable capture of the variance of task content of occupations across countries, but also gives more insight into the within-occupation heterogeneity. Since there is no survey data on the task content of occupations in Tunisia, we use the country-specific RTI at the two-digit ISCO-88 occupation level predicted by Lewandowski et al. (2020).

2.2 Tunisia's labour force survey

The data used for this paper are cross-sectional data from the National Population and Employment Survey (Enquête Nationale sur la Population et l'Emploi—ENPE). Through an agreement with the Tunisian National Statistics Institute (INS), we were able to gain access to three waves of data on labour market and household conditions from 2000, 2010, and 2017. In addition to labour market conditions, we have obtained access to data on wages and benefits.

The annual ENPE survey was first conducted in 2000 to provide information on the labour market, household composition, and employment policy. For these purposes, the survey is divided into two main modules. The first module provides demographic information on all members of the household, including gender, age, relationship with the householder, marital position, education, working status, and employment sector. The second module describes the working conditions and, exceptionally for paid workers, the remuneration (including net salary, assurance, allowance, and other benefits). Therefore, our analysis will mainly use the data set of employees. For comparison purposes, some analyses will also be conducted on the full data set of all workers.

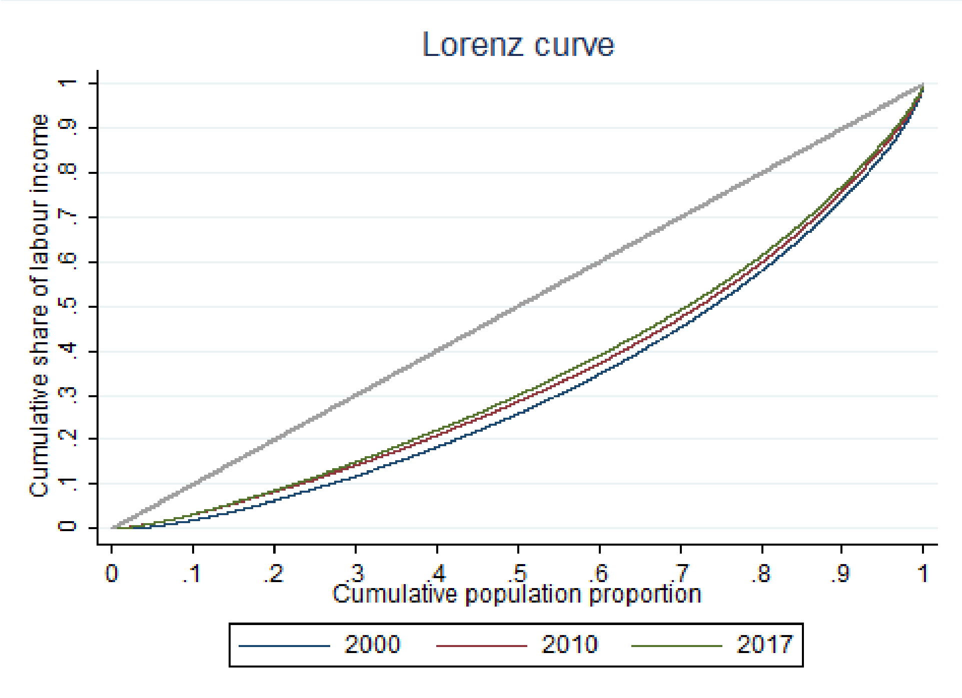
Among the three waves of the survey to which we have access, two waves (2000 and 2010) use NNP-97 (National Nomenclature of Professions 1997), corresponding to ISCO-88; the third wave, in 2017, uses NNP-14, corresponding to ISCO-08. Therefore, we first mapped the NNP to the corresponding ISCO, then ISCO-08 to ISCO-88. The NNP is highly compliant with ISCO, except that it does not further divide the agricultural and fishery occupational group into skilled and subsistence workers. All agricultural and fishery workers (NNP) were classified as skilled workers (group 61, ISCO). This classification is acceptable in our case because the survey only covers employees' earnings, while subsistence workers tend to be self-employed. Our second remark relates to the conversion from ISCO-08 to ISCO-88. For some ISCO-08 occupations that have various ISCO-88 equivalents, we chose the ISCO-88 equivalent that has the highest number of employees recorded in 2010. We observed that all ISCO-08 agricultural workers (occupations 6111–6223) were classified as ISCO-88 general managers in agriculture (occupations 1311–1312). Given that the agricultural workers have high RTI (measured by the country-specific RTI), putting them among the non-routine jobs like managers can be problematic. Therefore, to convert these occupations we use the earnings distribution and other workers' features relating to the position, such as workplace, contract types, and payment methods. Since occupations were precisely recorded at the four- or five-digit level, eventually we were able to merge the survey data with task measures at the four-digit ISCO-88 level.

3 Changes in job distribution and earnings inequality

3.1 General trends

Labour income inequality in Tunisia has decreased significantly over the past two decades, from 0.353 in 2000 to 0.294 in 2017. The trends in earnings inequality reflect two episodes: before and after the Revolution. The first period witnesses a rapid fall in earnings inequality, with the Gini index dropping by 4 percentage points over ten years. This reduction halved to around 2 percentage points in the second period. The Lorenz curves in Figure 1 provide an illustration of these trends.

Figure 1: Lorenz curves showing trends in labour income inequality



Source: authors' illustration based on ENPE data.

While the reduction is clear at the aggregate level, there is also evidence to suggest that the reduction in inequality did not affect all workers in the same way. On a macro level, we see that the variance in earnings may have fallen considerably from 2000 to 2010, but this improvement was followed by an increase in 2017 as compared to 2010. In fact, the difference between earnings in the bottom 50th (median) to 10th percentiles decreased more than those in the top 90th to 50th percentile (Table 1). The earnings gap between the 90th and 50th percentiles narrowed mostly during the post-Revolution period, whereas the earnings gap between the 90th and 10th percentiles contracted more in the pre-Revolution period. As we will argue in later sections, this decrease of inequality mainly came from the improvement of wages for low-wage workers and, to a lower extent, medium-wage workers.

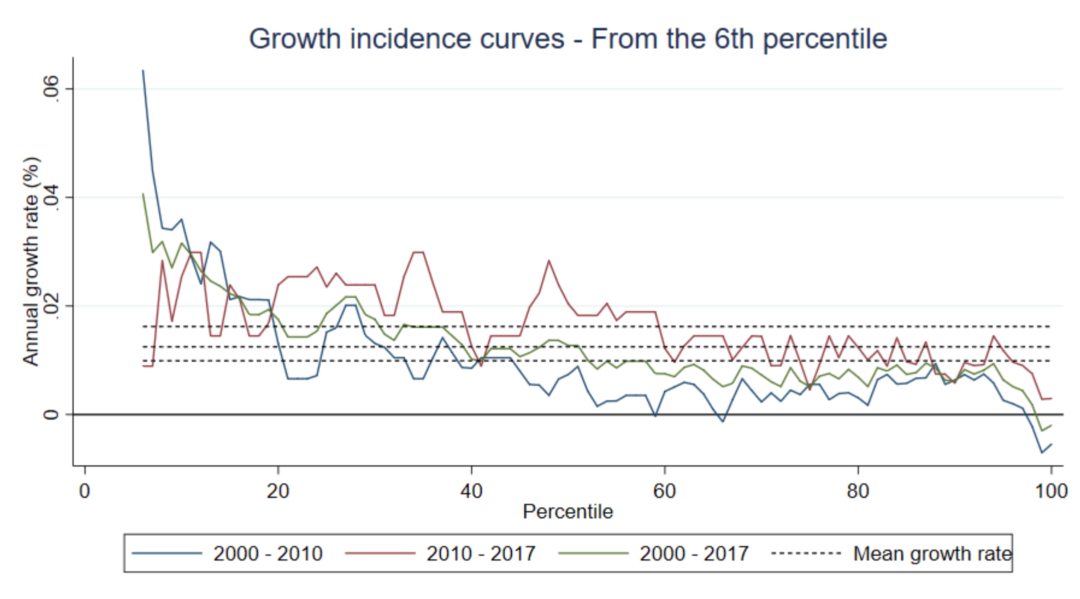
Table 1: Summary inequality indices and interquantile ratios

	Summary indices				Interquantile ratios		
	2000	2010	2017		2000	2010	2017
Var	0.645	0.384	0.429	p90/p10	1.636	1.422	1.283
Gini (log)	0.098	0.074	0.069	p90/p50	0.847	0.832	0.772
Gini	0.355	0.315	0.295	p50/p10	0.788	0.590	0.511

Source: authors' illustration based on ENPE data.

Examining the earning growth by percentile (Figure 2), we see a high growth in low wages from 2000 to 2010 (the lowest decile), but a net loss of earnings in low-wage jobs in the 2010–17 period. We also see opposite patterns for high-income earners, confirming that for the period prior to the Revolution we observed a reduction in growth of inequality, while after the Revolution we have observed some increasing variability of job growth across the earnings distribution. For the rest of the working population, growth was relatively flat in the pre-Revolution period, but increasing in the post-Revolution period. As such, some of the polarization we would expect to observe in the second period is hampered by growth in middle-wage occupations.

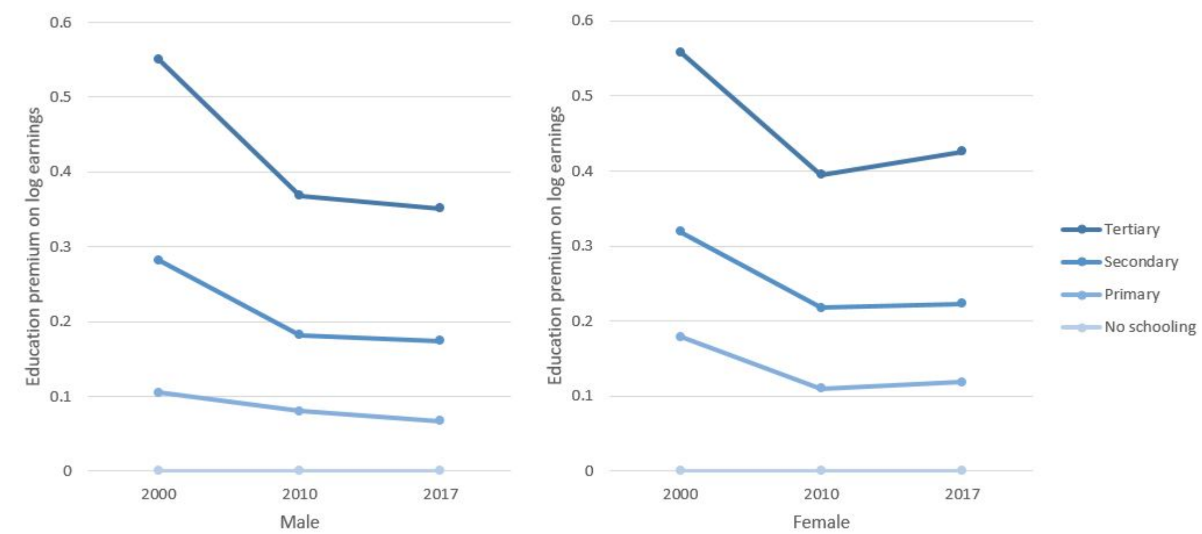
Figure 2: Growth incidence curves of the wage distribution



Source: authors' illustration based on ENPE data.

The decreasing trends of earnings inequality were congruent with the substantial decline in the education premium. While the supply of highly educated workers was and remained high, the demand for jobs in more productive and high-earning sectors stagnated (Marouani and Mouelhi 2016). The unemployment rate of Tunisian graduates soared from 10.4 per cent in 2001 to 22.9 per cent in 2010 (Adel 2013: 45–75) and 30 per cent in 2017 (Kthiri 2019). This explanation, based on the interplay between supply and demand for skills, is symmetric to what is witnessed by the most developed countries, according to Autor (2014).[3] As a result, the education premium associated with high-earning jobs decreased for men and women (Figure 3). In 2000, men and women educated at tertiary levels gained, respectively, 30 and 20 percentage points of a premium above those who had a secondary level of education. This difference had reduced to 10 percentage points by 2017.

Figure 3: Change in the education premium on log labour earnings by gender



Source: authors' illustration based on ENPE data.

[3] Furthermore, in Tunisia most highly educated workers prefer government to private sector jobs for reasons associated with stability and job-related benefits.

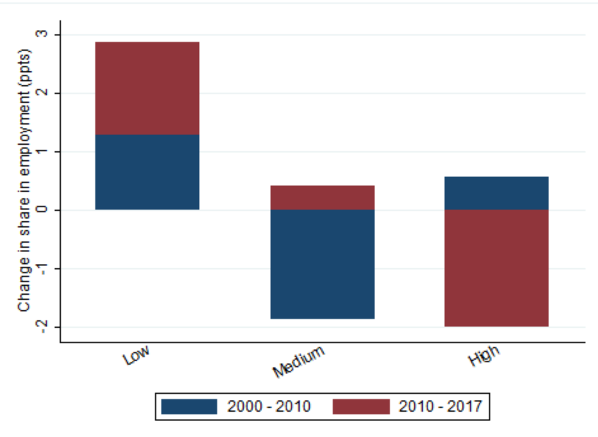
Although the education premium has been decreasing very sharply since 2000 (Figure 3), this movement slowed down for men and reversed for women. Prior to the Revolution, the education premium was higher for women than for men at any level of education. In line with the literature on gender and earnings, this suggests that education levels were a more important predictor of earnings for women than for men. For Tunisian wage earners, the Revolution levelled gender-related differences due to the returns to education. The reduction in the education premium finding suggests that not only were workers with different levels of education converging in terms of wages, but that this was also the case between males and females.

3.2 Structural change: sectors, occupations, and skill distributions

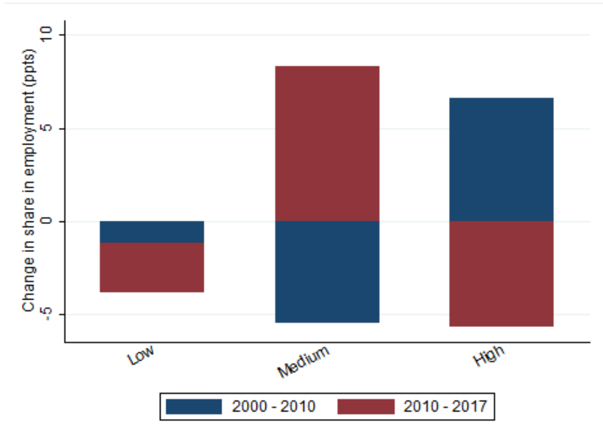
The trends in earnings inequality show some underlying heterogeneity. One of the reasons for these changes is the evolving share and earnings associated with occupations. When we look at the three skill group levels for all workers (Figure 4b) we find some stable results over the whole period of investigation and some that vary with the sub-period.[4] The share of low-skilled workers decreased between 2000 and 2017, with an acceleration after 2010. For medium- and high-skilled workers we have an inversion of trends: while high-skill workers were progressing at the expense of medium-skilled workers before 2010, high-skill jobs were reduced while medium-skill jobs increased in the second period. For wage earners only (Figure 4a), Tunisia witnessed an increase for unskilled and a decrease for medium-skilled workers in both periods, although the magnitudes differ. This means that self-employed workers, whose share increased in the Tunisian labour force, were mainly medium-skilled workers.

Figure 4: Changes in employment shares by skill levels

(a) Paid employees



(b) All workers



Source: authors' illustration based on ENPE data.

When we look at the one-digit occupational level (Table 2, illustrated in Figure A3), we find that clerks and technicians were the biggest losers in terms of jobs with an acceleration after the Revolution. The decline of clerical jobs may be attributed to routinization, since this group includes many high-RTI jobs such as keyboard-operating clerks and numerical clerks. Technicians and associated professionals whose share was slightly increasing in the first period were characterized by a significant decrease after 2010. This is due to shrinking activity in the transport and telecom sectors after the Revolution (Table A1). On the opposite side, skilled agricultural workers and services employees were the main beneficiaries in terms of employment creation. For category 5 (service workers), the number of security-related workers almost doubled between 2010 and 2017, while it decreased slightly between 2000 and 2010 (Table A2). This increase after the Revolution was due to the significant increase in security forces hiring

[4] The classification of broad skill levels is adapted from the ILO's classification. Groups 1–3 are labelled as high skill level; groups 4, 5, 7, and 8 as medium skill level; and groups 6 and 9 as low skill level.

(policemen, national guard, etc.). Shop salespersons also increased significantly, as well as housekeepers and restaurant service workers.

Table 2: Descriptive statistics by occupational groups at the one-digit level

	Level			Growth rate	
	2000	2010	2017	2000–10	2010–17
Panel A: share of employment (%)					
1 Managers	3.53	3.39	3.20	–0.40	–0.81
2 Professionals	10.74	11.22	10.94	0.44	–0.36
3 Technicians	6.68	6.90	5.36	0.32	–3.54
4 Clerks	9.79	7.51	5.38	–2.62	–4.66
5 Services	10.12	10.91	14.35	0.76	3.99
6 Skilled agricultural	3.88	3.11	4.74	–2.17	6.19
7 Trade workers	14.85	13.79	13.92	–0.73	0.13
8 Machine operators	15.28	15.97	14.93	0.44	–0.95
9 Elementary	25.15	27.19	27.16	0.78	–0.01
B. Mean weekly earnings (constant 2010 prices)					
1 Managers	196.71	209.99	195.36	0.66	–1.03
2 Professionals	163.25	175.12	180.53	0.70	0.44
3 Technicians	123.32	124.08	139.01	0.06	1.64
4 Clerks	103.81	102.96	110.73	–0.08	1.05
5 Services	84.74	80.97	92.20	–0.45	1.87
6 Skilled agricultural	45.17	51.99	64.04	1.42	3.02
7 Trade workers	70.00	81.67	92.33	1.55	1.77
8 Machine operators	70.02	74.70	84.34	0.65	1.75
9 Elementary	51.41	59.29	75.54	1.44	3.52

Note: growth refers to compound annual growth rate for the periods indicated.

Source: authors' illustration based on ENPE data.

As shown by Figure A2, the sectoral distribution of gross domestic product (GDP) helps understand some of the previous dynamics. While between 2000 and 2010 the share of agriculture in GDP continued decreasing to less than 10 per cent of GDP, there was a slight relaunch of agriculture after the Revolution as this sector has probably been the least disrupted by social tensions. Deindustrialization in favour of services continued between 2000 and 2015.[5] Finally, the share of government, which was quite high in Tunisia, started increasing again after the Revolution due to social and political pressures.

Wage dynamics were mainly in favour of the two lowest occupation groups, agricultural and elementary workers (Table 2). The group 'technicians and associate professionals' was the only exception. Another interesting result is the fall in managers' wages. This is a non-standard result in comparison to the literature.

3.3 Polarization tests

The above preliminary description of the Tunisian data set suggests a potential consistency with Autor et al.'s routinization hypothesis (2003). From 2000 to 2017, the labour market in Tunisia witnessed a strong decrease of high routine manual occupational groups such as clerical, craft and related trade jobs, and manufacturing jobs. In the meantime, the average weekly earnings of low-skilled and non-routine jobs such as services and elementary occupations increased significantly (Table 2). The descriptive statistics, however, reveal also different patterns in the occupational evolution; for example, the decreased number of technical jobs, the contrasting employment share changes of the agricultural group over the pre- and post-Revolution periods, or the earnings degradation of managers after the Revolution. These labour market dynamics resulted from the complex interplay between various factors, among them computerization of routine jobs, structural transformation, decline of the education premium, and

[5] This will be updated later with data from 2017.

the 2011 Revolution. Therefore, it is not straightforward to claim a preeminent role for the routinization hypothesis in the evolution of the labour market in Tunisia.

The job polarization test proposed by Goos and Manning (2007) is a popular way to verify the routinization hypothesis. As the middle-income jobs are usually the most routine-intensive, the decrease of their share leads to a U-shaped pattern of employment evolution conditional on the initial wage level. More precisely, the specification is as follows:

$$\Delta EmploymentShare_i = \beta_0 + \beta_1 Earnings_{i,t-1} + \beta_2 Earnings^2_{i,t-1} \quad (1)$$

If there exists a polarization pattern, the coefficient of the linear term should be found significantly negative, while the coefficient of the quadratic term significantly positive.

The decrease in the demand for middle-skill jobs should result in a decrease in wages at the middle of the distribution relative to the bottom and the top. In other words, if a polarization of jobs exists, changes in wages should also follow the same U-shaped pattern as changes in employment share. Hence, Sebastian (2018) extended this specification to the relationship between wage growth and the initial wage level:

$$\Delta \log Earnings_i = \beta_0 + \beta_1 Earnings_{i,t-1} + \beta_2 Earnings^2_{i,t-1} \quad (2)$$

Table 3 presents our quadratic regressions of changes in employment share and log mean earnings on the initial level of log mean earnings. The regressions using the median earnings as in Goos and Manning (2007) are presented in Table A3. Although no significant evidence of employment polarization is found in Tunisia, the regression of log earnings growth on the initial log mean earnings provides support for the earnings polarization in the first period. Despite the significant regression estimates, the plot of the changes in log earnings over skill percentiles (Figure 5b) and the fitted plot (Figure 6) show an L-shaped pattern with the increase of earnings at the lower end of the distribution and the stagnancy of earnings at the upper end of the distribution.

Table 3: Job and earnings polarization tests

	Change in employment share			Change in log mean earning		
	2000–10	2010–17	2000–17	2000–10	2010–17	2000–17
Initial log mean earnings	1.412	–1.934	0.933	–2.192***	–0.988*	–2.114***
	(0.915)	(2.670)	(1.591)	(0.268)	(0.543)	(0.357)
Sq. initial log mean earnings	–0.167	0.183	–0.139	0.228***	0.086	0.198***
	(0.109)	(0.294)	(0.186)	(0.033)	(0.060)	(0.043)
Constant	–3.004	4.826	–1.571	5.280***	2.778**	5.601***
	(1.919)	(5.990)	(3.363)	(0.522)	(1.230)	(0.735)
Observations	103	102	101	103	102	101
R-squared	0.027	0.068	0.064	0.613	0.441	0.731
Adj. R-squared	0.00735	0.0488	0.0451	0.605	0.429	0.726
F-test	0.308	0.0516	0.137	0.000	0.000	0.000

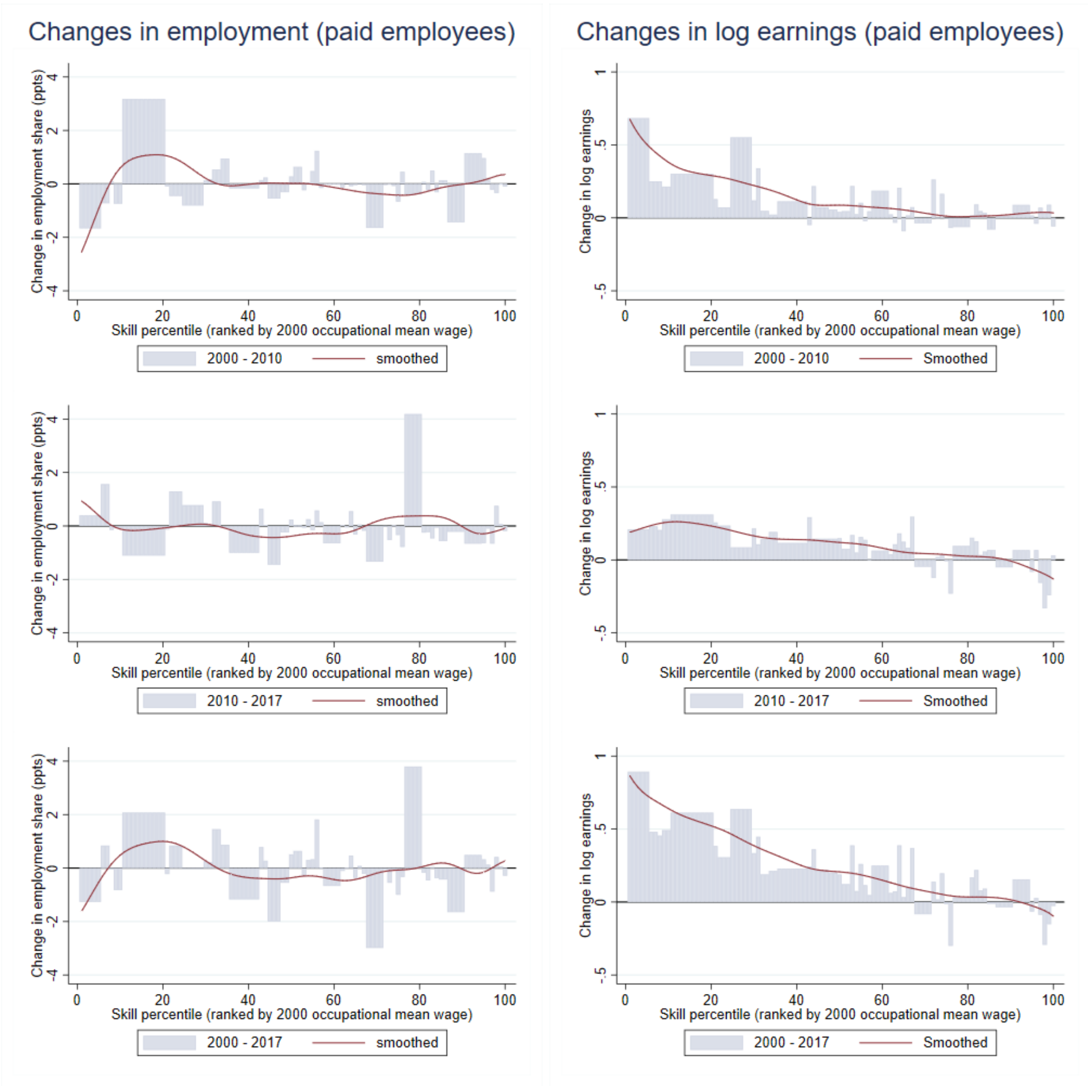
Note: robust standard errors in parentheses *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Source: authors' illustration based on ENPE data.

As shown in Figure 4b, the trend of employment shares of the three skill groups changes drastically when including self-employed. Indeed, self-employment represents an important share (around 30 per cent) of total employment in Tunisia. Therefore, we imputed earnings for self-employed using the multiple imputation method and replicated the same specifications for the all-workers data set (including paid employees and self-employed with and without employees). The results (Table A4) do not differ much from the regressions with the paid employees data set, except for the weakly negative linear relationship between change in log mean earnings and the initial log mean earnings in the second period. However, if we bear in mind that the imputation might suffer an upward bias because average earnings of self-employed tends to be lower than employees in the same occupations, it comes as no surprise that the weak quadratic relationship turns into a linear relationship.

Figure 5: Change in log earnings and employment share by skill percentiles

(a) Employment share (b) Log earnings



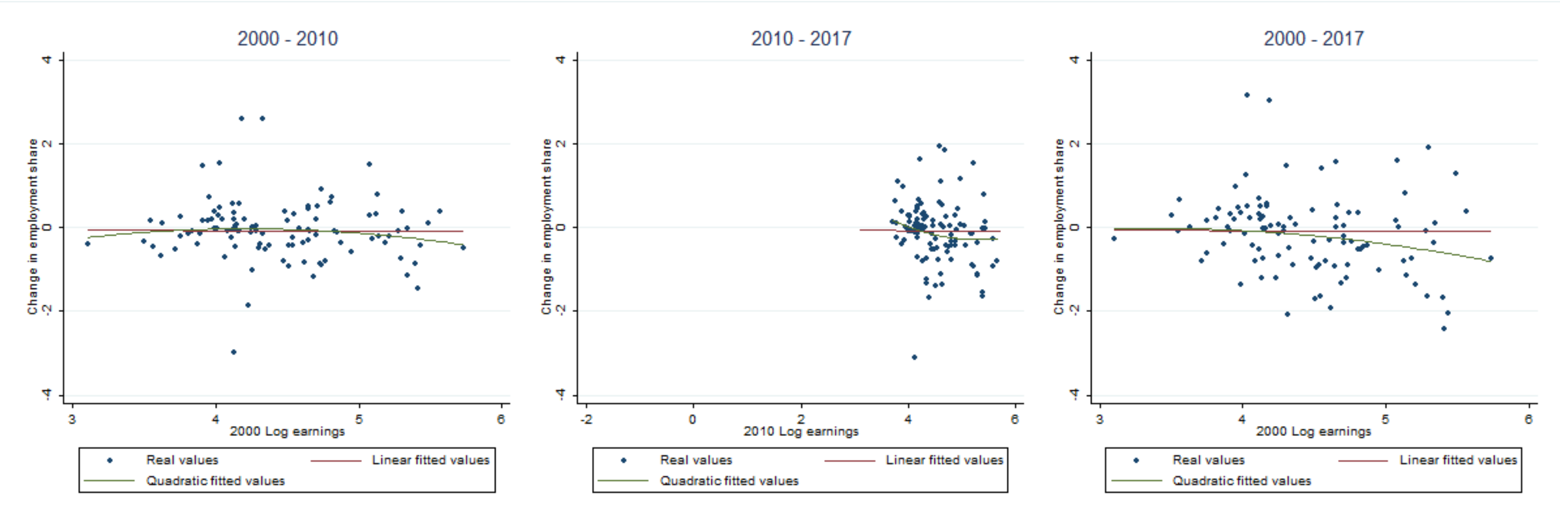
Source: authors' illustration based on ENPE data.

One might think that the polarization is crowded out by the employment trend due to the structural transformation from agriculture to manufacturing. To test for this potential, we remove the agriculture sector from the regressions. As shown in Table A5, our results remain stable even after the removal of this sector.

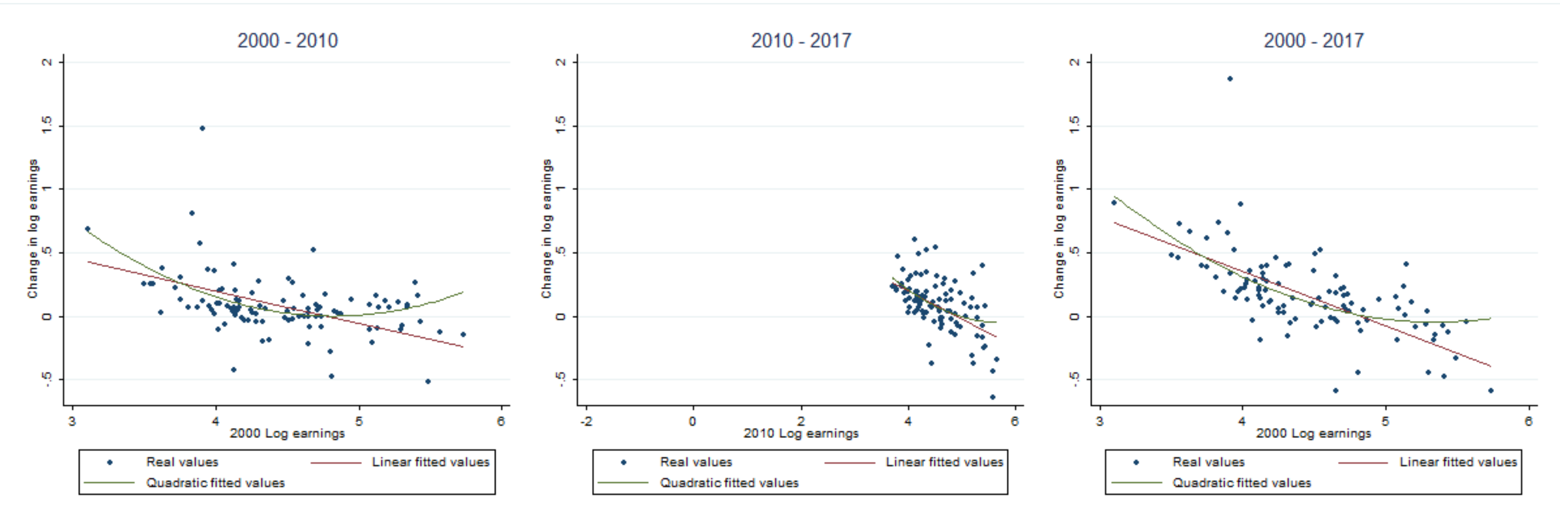
Our analysis also takes into account the effect of the public sector, since its role as jobs provider has increased sharply in the aftermath of the Revolution. In order to soften social tensions caused by youth unemployment and to maintain security, public recruitment focused mostly on graduates and protection services. The number of employees recruited in the public sector has increased by 47.6 per cent from 2010 to 2017, while the share of the public administration fluctuated around 20 per cent of the employee population in Tunisia. [6] After excluding the public sector from the analysis, we still do not find any sign of job polarization, but even a reverse U-shaped pattern in the first period (Table A6).

[6] Authors' calculation based on INS data.

Figure 6: Fitted plots of job and earnings polarization
(a) Job



(b) Earnings



Source: authors' illustration based on ENPE data.

4 Task-based analysis

4.1 Distributional changes and task content

So far we have examined the polarization phenomenon in Tunisia's labour market and found an earnings polarization at the lower end of the distribution, but failed to confirm job polarization. In this section, we further investigate the routinization hypothesis using the different measures of the RTI of jobs. Table 4 provides an overall comparison between the two indices. Both were negatively correlated with the average log earnings of the job, but the country-specific RTI was more correlated than the O*NET RTI. We then plot the distribution of the task intensity over skill percentiles ranked by occupational mean log earnings in Figure 7. The distributions of the two indices, despite their stability over time, were quite different. Panel (a) shows a monotonically declining curve of RTI over skill percentiles, and panel (b) shows an inverted U-shape curve. In other words, the country-specific RTI indicates that high-RTI jobs are rather low-paid, while the O*NET RTI suggests that high-RTI jobs are located at the middle of the earnings distribution.

Table 5 summarizes the change in average RTI over time. For paid employees, the average country-specific RTI increased over the two periods, while the O*NET RTI increased only during the first period and then declined. For all workers, the average RTI measured by the country-specific and the O*NET RTI both witnessed a decline in the first period and a rebound in the second.

Table 4: Correlation between log earnings, O*NET RTI, and country-specific RTI

	Log earnings	Country-specific RTI	O*NET RTI
Log earnings	1.0000		
Country-specific RTI	–0.5413	1.0000	
O*NET RTI	–0.4029	0.7232	1.0000

Source: authors' illustration based on ENPE data.

Table 5: Average RTI over time

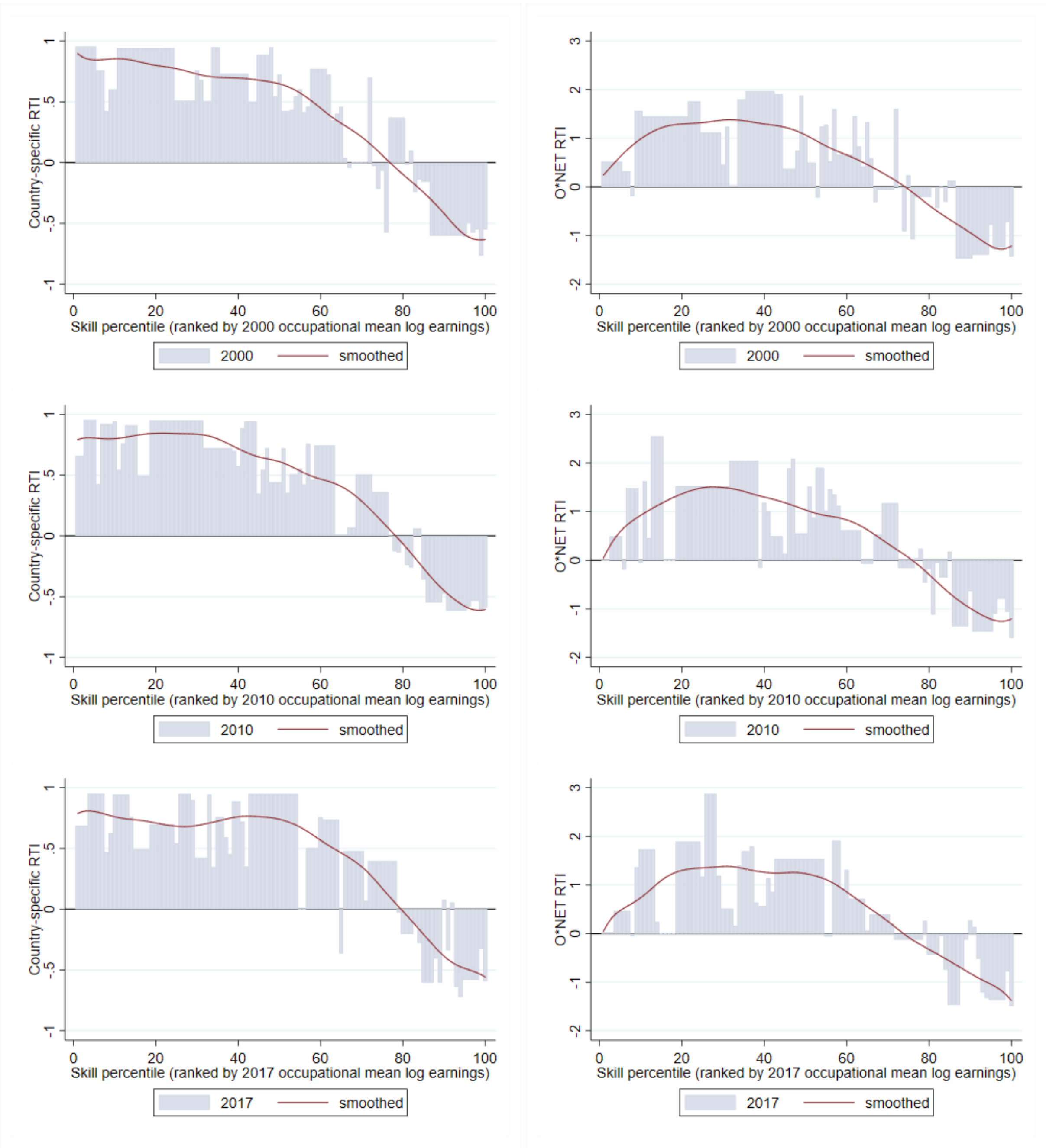
	Paid workers			All workers		
	2000	2010	2017	2000	2010	2017
Country-specific RTI	0.401	0.416	0.441	0.428	0.360	0.421
O*NET RTI	0.529	0.602	0.567	0.449	0.321	0.403

Source: authors' illustration based on ENPE data.

Figure 7: RTI over skill percentiles

(a) Country-specific RTI

(b) O*NET RTI



Source: authors' illustration based on ENPE data.

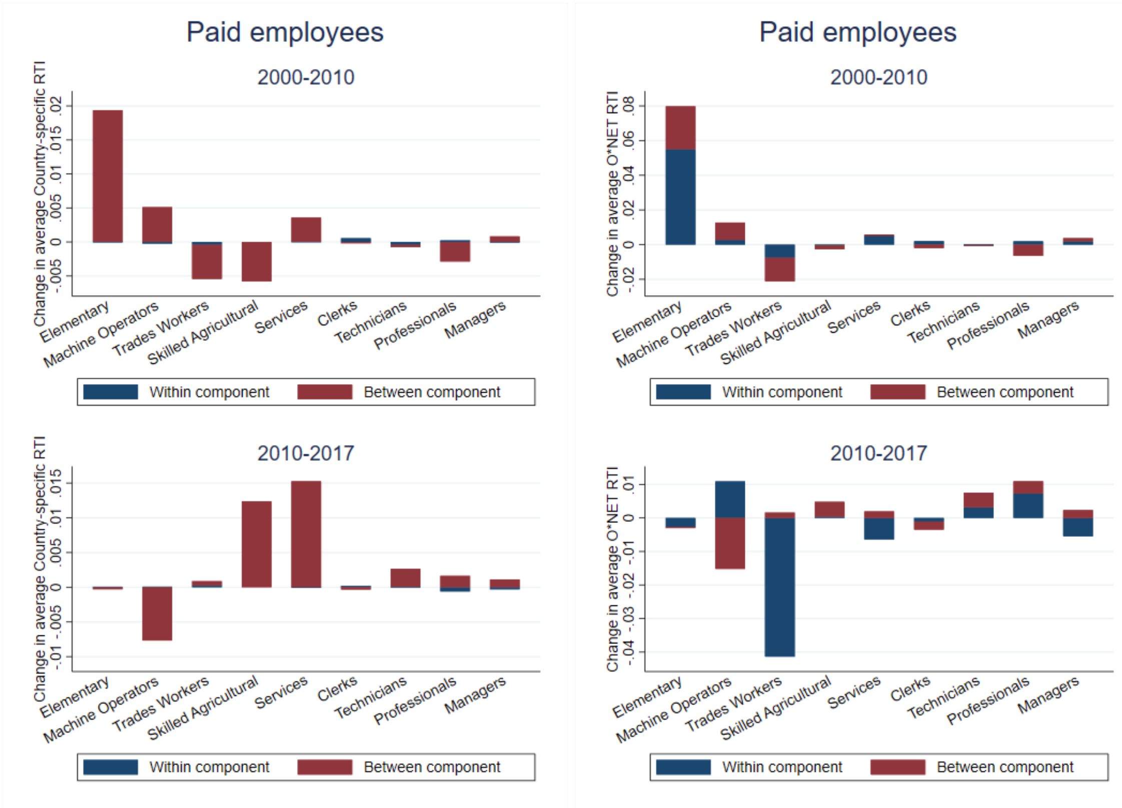
To understand the increasing trend of Tunisia's RTI, we disaggregate the overall change in average RTI into the effect of the change of the occupational structure within each one-digit occupation (within effect) and the effect of changes in the share of each occupation at the one-digit level (between effect). This analysis is repeated for sectors. The decomposition is expressed as follows, where the subscript i

represent alternatively one-digit occupations or sectors:

$$\begin{aligned}
\Delta\overline{RTI} &= \sum \overline{RTI}_{i1} * w_{i1} - \sum \overline{RTI}_{i0} * w_{i0} \\
&= \sum \overline{RTI}_{i1} * w_{i1} - \sum \overline{RTI}_{i0} * w_{i1} + \sum \overline{RTI}_{i0} * w_{i1} - \sum \overline{RTI}_{i0} * w_{i0} \\
&= \underbrace{\sum (\overline{RTI}_{i1} - \overline{RTI}_{i0}) * w_{i1}}_{\text{Within effect}} + \underbrace{\sum \overline{RTI}_{i1} * (w_{i1} - w_{i0})}_{\text{Between effect}}
\end{aligned}$$

The results of our decomposition are presented in Figures 8 and 9. Both RTIs increased mostly due to the increase of elementary jobs—labourers in construction and manufacturing—in the first period. However, the contribution of elementary occupations to changes in average country-specific RTI is due to the 'between effect', while the contribution of elementary occupations to changes in average O*NET RTI is due to the 'within effect'. This results from the differences of the two RTIs in the agriculture sector and elementary occupations. Occupations in agriculture are considered to have high RTI using the country-specific RTI: skilled agricultural workers (group 61) had an RTI of 0.76 and agricultural labourers (group 92) had an RTI of 0.95. Measured by the O*NET RTI, the two scores shrink to 0.29 and 0.52, respectively (weighted average using the 2000 employment share). Labourers in construction, mining, and manufacturing (group 93) have high RTI when calculated by O*NET RTI (1.55), but much lower RTI when measured by country-specific RTI (0.95).

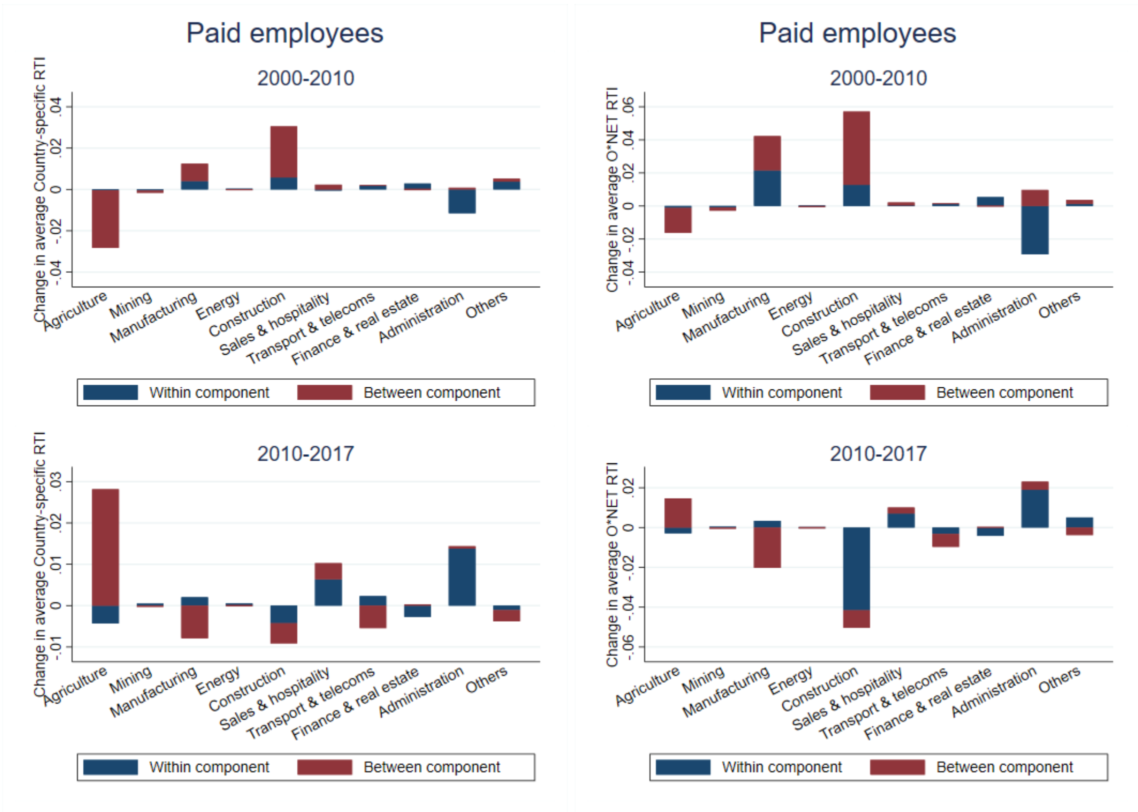
Figure 8: Decomposition of changes in average RTI by occupational group
(a) Country-specific RTI (b) O*NET RTI



Source: authors' illustration based on ENPE data.

Figure 9: Decomposition of changes in average RTI by industry

(a) Country-specific RTI (b) O*NET RTI



Source: authors' illustration based on ENPE data.

Although the average country-specific RTI kept increasing in the aftermath of the Revolution, the drivers at the one-digit occupational level were not the same. After 2010, the manufacturing industry and construction—the main drivers of RTI before the Revolution—now negatively contributed to the average RTI due to a decrease in the share of plant and machine operators. Nevertheless, the higher demand for skilled agricultural workers and protective service workers more than compensated for the former, and aggregate country-specific RTI increased between 2010 and 2017. On the opposite side, we observed a declining trend of the O*NET RTI in the second period because of the occupational group trade workers, which has an O*NET RTI of 1.3 and a country-specific RTI of 0.84.

In the next step, we apply the same specification as in the polarization tests to study the correlation between RTI and the dynamics of employment and earnings in Tunisia. We use data at the three-digit occupational level for the O*NET RTI and data at the two-digit occupational level for the country-specific RTI. The models are as follows:

$$\Delta EmploymentShare_i = \beta_0 + \beta_1 RTI_{i,t-1} \tag{3}$$

$$\Delta EmploymentShare_i = \beta_0 + \beta_1 RTI_{i,t-1} + \beta_2 RTI^2_{i,t-1} \tag{4}$$

$$\Delta \log Earnings_i = \beta_0 + \beta_1 RTI_{i,t-1} \tag{5}$$

$$\Delta \log Earnings_i = \beta_0 + \beta_1 RTI_{i,t-1} + \beta_2 RTI^2_{i,t-1} \tag{6}$$

The regressions results for employment share change and log earnings change are presented in Tables 6 and 7, respectively. The insignificant point estimate of $RTI_{i,t-1}$ and $RTI^2_{i,t-1}$ for the employment share change comes as no surprise, since we did not find any evidence of job polarization in the previous section. For the change in log earnings, all linear terms are positively significant in both periods. This implies that the higher-RTI occupations tended to have larger increases in earnings over time, which is at odds with the routinization hypothesis. The country-specific RTI is more associated with income variation than the O*NET RTI, but the direction of the estimates is similar. These results confirm the absence of job polarization and the L-shaped evolution of earnings conditional on the initial earnings that we observed in Section 3.

Table 6: OLS regression of change in employment share on the initial level of RTI

	2000–10	2010–17	2000–17	2000–10	2010–17	2000–17
Country-specific RTI	1.164	0.230	1.592*	0.049	0.757	0.771
	(1.082)	(0.455)	(0.928)	(0.271)	(0.462)	(0.634)
Sq. country-specific RTI				2.885	–1.365	2.123
				(2.163)	(1.376)	(2.471)
Constant	–0.249	–0.145	–0.466	–1.077	0.263	–1.076
	(0.429)	(0.289)	(0.679)	(0.698)	(0.648)	(1.211)
Observations	26	26	26	26	26	26
R-squared	0.113	0.013	0.166	0.254	0.101	0.225
Adj. R-squared	0.0759	–0.0284	0.131	0.189	0.0232	0.158
F-test	0.293	0.618	0.0991	0.424	0.280	0.102
O*NET RTI	0.651	–0.082	0.654	0.322	0.120	0.438
	(0.528)	(0.234)	(0.430)	(0.347)	(0.147)	(0.256)
Sq. O*NET RTI				0.611	–0.303	0.401
				(0.365)	(0.252)	(0.482)
Constant	–0.129	0.000	–0.176	–0.756	0.328	–0.587
	(0.443)	(0.340)	(0.632)	(0.517)	(0.544)	(1.037)
Observations	26	26	26	26	26	26
R-squared	0.129	0.006	0.102	0.257	0.102	0.146
Adj. R-squared	0.0927	–0.0351	0.0649	0.192	0.0243	0.0713
F-test	0.230	0.728	0.141	0.259	0.392	0.235

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

Source: authors' illustration based on ENPE data.

Table 7: OLS regression of change in log earnings on the initial level of RTI

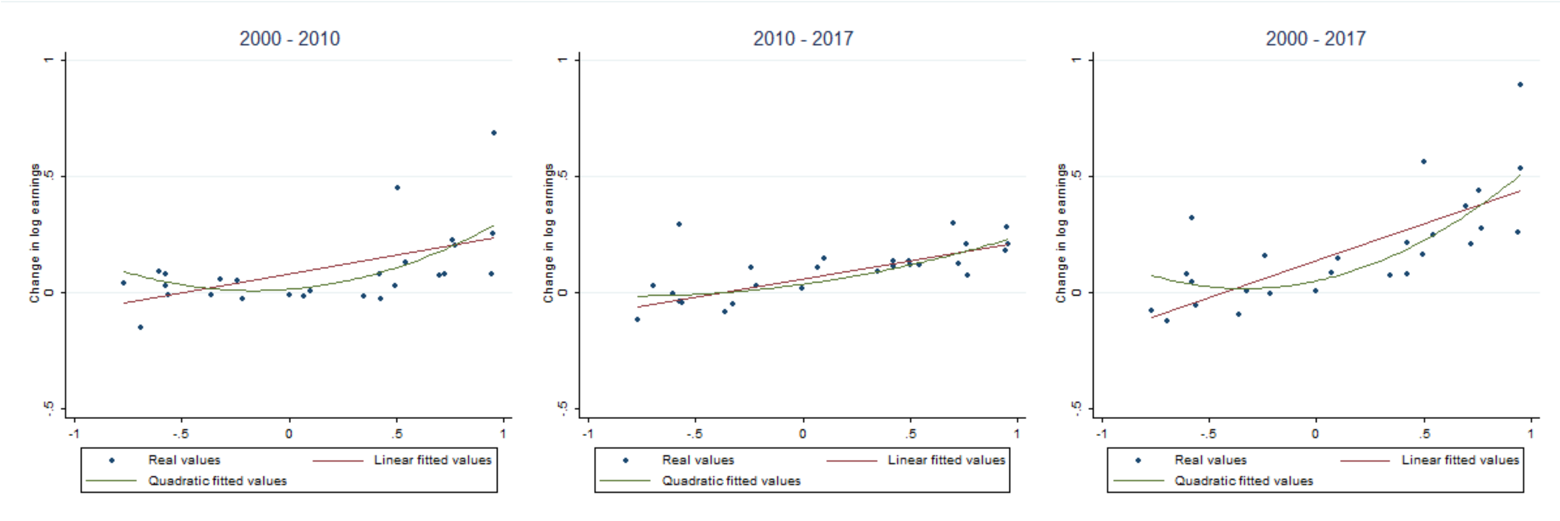
	2000–10	2010–17	2000–17	2000–10	2010–17	2000–17
Country-specific RTI	0.161**	0.159***	0.314***	0.074	0.128***	0.199***
	(0.066)	(0.029)	(0.079)	(0.059)	(0.016)	(0.063)
Sq. country-specific RTI				0.226	0.079	0.298*
				(0.165)	(0.047)	(0.168)
Constant	0.079**	0.059***	0.136***	0.014	0.035**	0.050
	(0.037)	(0.012)	(0.044)	(0.063)	(0.016)	(0.065)
Observations	26	26	26	26	26	26
R-squared	0.223	0.701	0.474	0.312	0.736	0.561
Adj. R-squared	0.191	0.689	0.452	0.252	0.713	0.523
F-test	0.022	0.000	0.001	0.033	0.000	0.000
O*NET RTI	0.055**	0.067***	0.117***	0.063*	0.067***	0.128***
	(0.027)	(0.019)	(0.039)	(0.031)	(0.012)	(0.037)
Sq. O*NET RTI				–0.014	–0.001	–0.020
				(0.038)	(0.016)	(0.049)
Constant	0.115***	0.084***	0.200***	0.129*	0.085***	0.221**
	(0.041)	(0.013)	(0.049)	(0.074)	(0.022)	(0.090)
Observations	26	26	26	26	26	26
R-squared	0.096	0.485	0.242	0.104	0.485	0.250
Adj. R-squared	0.0587	0.464	0.210	0.0256	0.441	0.185
F-test	0.049	0.002	0.006	0.125	0.000	0.008

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

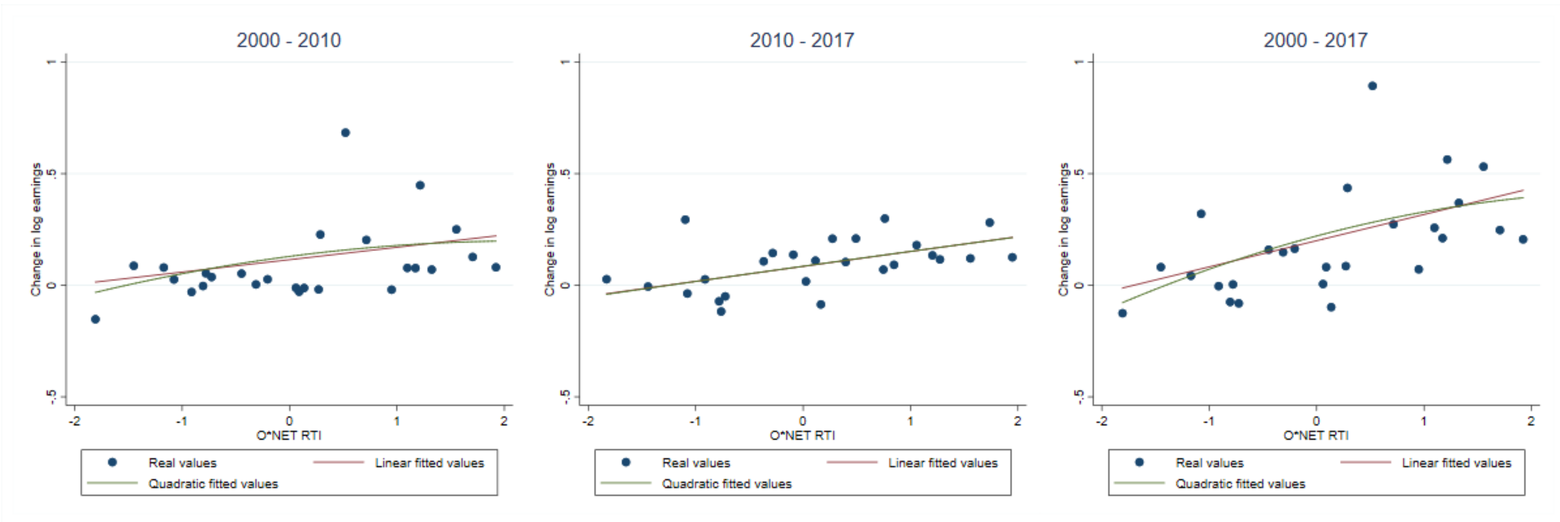
Source: authors' illustration based on ENPE data.

In Figure 10 we plot the real change in log mean earnings as well as linear and quadratic fitted values against the O*NET RTI (panel (a)) and the country-specific RTI (panel (b)), which allows us to visualize the positively linear relationship between earnings growth and RTI.

Figure 10: Effect of RTI on occupational log mean earnings
(a) Country-specific RTI



(b) O*NET RTI



Source: authors' illustration based on ENPE data.

4.2 Shapley decomposition and RTI's contribution to the earnings inequality

This section investigates the contribution of occupational variation and the role of task content in earnings inequality evolution in Tunisia's labour market. We apply the Shapley decomposition method, which allows us to decompose non-additively decomposable inequality indices such as the Gini index into between-occupation and within-occupation contributions.

As reported in Table 8, about half of the overall inequality can be attributed to the differences between occupations, or the specific characteristics of the occupational groups. While the decline in inequality during the first period is entirely driven by within-occupation inequality, the smaller decline in the second period was primarily driven by lower between-occupation inequality. The pre-Revolution within-occupation changes in inequality seem to resonate with the decreasing education premium resulting from the oversupply of high-skilled workers, whereas the post-Revolution between-occupation changes in inequality are probably linked to the lower share of top-paid occupational groups described in Table 2.

Table 8: Gini decomposition: occupation and task content

	Actual			Share constant			Means constant		
Shapley decomposition	2000	2010	2017	2000	2010	2017	2000	2010	2017
1 Overall Gini	0.354	0.317	0.295	0.354	0.320	0.303	0.354	0.327	0.331
2 Between occupations	0.177	0.176	0.139	0.177	0.176	0.147	0.177	0.187	0.182
Ratio of (2) to (1) (%)	50%	55%	47%	50%	55%	48%	50%	57%	55%
3 Within occupations	0.177	0.142	0.157	0.177	0.144	0.156	0.177	0.139	0.148
Ratio of (3) to (1) (%)	50%	45%	53%	50%	45%	52%	50%	43%	45%
4 Gini between occupations	0.252	0.237	0.194	0.252	0.239	0.204	0.252	0.251	0.246
Country-specific RTI									
5a Concentration index (-RTI)	0.238	0.221	0.173	0.238	0.221	0.184	0.238	0.238	0.233
Ratio of (5a) to (4) (%)	95%	93%	89%	95%	93%	90%	95%	95%	95%
*O*NET RTI*									
5b Concentration index (-RTI)	0.208	0.198	0.154	0.208	0.195	0.167	0.208	0.213	0.200
Ratio of (5b) to (4) (%)	82%	83%	80%	82%	82%	82%	82%	85%	82%

Source: authors' illustration based on ENPE data.

When we keep the employment share of the occupations constant over time, the trends of the within and between effects remain unchanged. However, if the occupational mean earnings is instead kept constant, the contribution of occupational characteristics to the total inequality would increase by 2 percentage points in 2010 and 7 percentage points in 2017. In sum, the between-inequality changes were mostly driven by the changes in occupational mean earnings, which are increasing over time.

To study the role of task content in the between-occupations inequality evolution, we construct the RTI concentration index based on the approach of the Gini concentration index. The RTI concentration index measures the extent to which the distribution of occupational average earnings deviates from a perfectly equal distribution. The difference is that occupations are ranked by their RTI instead of their average earnings. If the ranking of occupational groups by RTI is similar to the ranking of occupational groups by average earnings, the RTI concentration index would be equal to the Gini index. In Table 8, the ratio between two indices follows the same trend as the between-occupations contribution resulting from the Shapley decomposition. More precisely, the share of inequality due to differences between occupations (measured by the RTI) was augmented during the first period and decreased substantially during the second period. The country-specific RTI explains better the Gini differences between occupations in comparison to the O*NET RTI.

5 Determinants of changes in earnings inequality

5.1 Methodology

While the Shapley method can be used to decompose the wage differentials between an unlimited number of subgroups into within and between effects, it does not allow further dividing these effects into the contribution of covariates. For the latter purpose, we use the RIF decomposition method developed by Firpo et al. (2011, 2018). Generalized from the conventional Oaxaca–Blinder decomposition, the RIF decomposition can be applied to any distributional statistics besides mean, such as median, variance, the Gini index, or interdecile ratios. The key idea is to replace the outcome variable Y by a RIF of the distributional statistic of interest. The influence function $IF(y;\nu;F)$ of a distributional statistic $\nu(F)$ tells us how much an individual observation affects that distributional statistic (Firpo et al. 2009). The $RIF(y;\nu;F)$ is then created by adding the statistic $\nu(F)$ to $IF(y;\nu;F)$ so that its expectation is equal to the statistic $\nu(F)$. Rios Avila (2019) provides a list of all distributional statistics and the corresponding RIF, together with the related literature for reference.

Suppose that we need to evaluate the changes in the wage distribution from period 0 (group 0) to period 1 (group 1). Let ν be the distributional statistic of interest; the difference in the distributional statistics between the two groups—the overall wage gap—is:

$$\begin{aligned}\Delta_O^\nu &= \nu(F_{Y_1|T=1}) - \nu(F_{Y_0|T=0}) \\ &= \underbrace{\nu(F_{Y_1|T=1}) - \nu(F_{Y_0|T=1})}_{\Delta_S^\nu} + \underbrace{\nu(F_{Y_0|T=1}) - \nu(F_{Y_0|T=0})}_{\Delta_X^\nu}\end{aligned}$$

where Δ_S^ν is the wage structure effect and Δ_X^ν is the composition effect. To construct the counterfactual distributional statistic $\nu(F_{Y_0|T=1})$, we follow the parametric reweighting procedure proposed by Firpo et al. (2018). Accordingly, the reweighting function is:

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

As our main purpose is to estimate the contribution of each covariate, we will take one more step by rewriting the wage structure and the composition effects as:

$$\begin{aligned}\Delta_S^\nu &= \mathbb{E}[X|T=1]^T(\gamma_1^\nu - \gamma_0^\nu) \\ \Delta_X^\nu &= (\mathbb{E}[X|T=1] - \mathbb{E}[X|T=0])^T\gamma_0^\nu\end{aligned}$$

where γ_1^ν and γ_0^ν are the estimated coefficients from a regression of $RIF(y_t;\nu)$ on X:

$$\gamma_t^\nu = (\mathbb{E}[X.X^T|T=t])^{-1}.\mathbb{E}[RIF(y_t;\nu_t).X|T=t], \quad t=0,1$$

In a nutshell, the RIF decomposition procedure consists of two stages. In the first stage, we decompose the inequality index of interest (the Gini index, the p90/p50 ratio, and the p50/p10 ratio) into a wage structure effect and a composition effect using a parametric reweighting approach. In the second stage, we divide the wage structure and the composition effects into the contribution of each covariate using the Oaxaca–Blinder method.

5.2 Results

As discussed in the previous sections, the change in the wage structure of the Tunisian labour market might be driven by various forces, such as routinization, public employment policies, uniform wage increases in the public sector, and service-led structural change (or deindustrialization). The above evidence shows that the devolution in the routine nature of jobs has not been the main driving force of the changes in earnings inequality over the last two decades. But how much did the changing nature of jobs contribute to inequality change, in comparison to other factors? To answer this question, we first decompose the changes in earnings inequality into wage structure and composition effects, then further divide these two effects into the contribution of observed determinants, including occupation, age, sex, education, public sector, and industry. The dummy variable for public sector can be thought of as a proxy for the effect of the trade union on inequality, since only trade unions in the public administration and enterprises have power over wage setting. Trade unions have less influence in the private sector.

The results of the RIF decomposition are presented in Tables 9 and 10. Although more than half of the specification errors, which measure the importance of departures from the linearity assumption of the RIF approximation (Firpo et al. 2018), are significant, they are relatively small when compared to the total changes of the distribution (except the case of the 90–50 gap in the first period). This implies that the reweighting RIF regression model performs relatively well at estimating the composition effects.

In general, the composition effect, or the changes in the distribution of workers' characteristics, does not directly contribute to the overall change in Gini coefficient (Table 9). The positive composition effect is entirely counteracted by the wage structure effect in the first period, while there is no total composition effect observed in the second period. Hence, it is the earnings structure effect, or the changes in return of the market to the characteristics, which contributes primarily to the overall change in earnings inequality. These results are also in line with our findings from the Shapley decomposition, which concluded that the earnings inequality changes were predominantly driven by the changes in occupational average earnings.

As shown in Figure 12, the change in the employment share of the public sector is the main determinant of earnings changes within the composition effect. The fall in low-paid jobs in the public sector directly leads to a fall in the average earnings of these jobs relative to the medium- and high-paid jobs. Consequently, the change in the public employment share has a disequalizing effect on the overall earnings inequality before the Revolution.

Moving to the detailed wage structure effects (illustrated in Figure 13), we find that the public sector is, again, the largest contributor to the coefficient effect in the first period. Its major and equalizing effect on total inequality, however, turns into a minor and disequalizing effect in the second period. Interestingly, if we look at the q50/q10 and q90/q50 ratios, the wage structure effect linked to the public sector becomes greater and acts in opposite directions on the two halves of the distribution: it increases the q50/q10 earnings gap while decreasing the q90/q50 one. Similarly, the favourable change in return of the market to the routine-intensive jobs has an equalizing effect on the total earnings distribution in the first period. In the second period, the coefficient effect relating to the RTI increases inequality among workers in the lower half of the earnings distribution, but decreases inequality among workers in the upper half of the earnings distribution. Finally, the education premium has no effect on inequality in the pre-Revolution decade, but a disequalizing effect on overall inequality as well as the q90/q50 and q50/q10 earnings gaps in the post-Revolution period.

Table 9: RIF decomposition of changes in Gini

	Country-specific RTI		O*NET RTI	
	2000–10	2020–17	2000–10	2020–17
Final F	0.316***	0.286***	0.316***	0.286***
	(0.001)	(0.001)	(0.001)	(0.001)
Initial I	0.360***	0.316***	0.360***	0.316***
	(0.002)	(0.001)	(0.002)	(0.001)
Total change (F–I)	–0.044***	–0.030***	–0.044***	–0.030***
	(0.002)	(0.001)	(0.002)	(0.001)
Reweighting decomposition				
Counterfactual C	0.389***	0.316***	0.388***	0.319***
	(0.006)	(0.001)	(0.005)	(0.001)
Total composition (C–I)	0.029***	0.000	0.028***	0.003***
	(0.005)	(0.000)	(0.004)	(0.001)
Total earnings structure (F–C)	–0.073***	–0.030***	–0.072***	–0.032***
	(0.006)	(0.001)	(0.005)	(0.001)
RIF aggregate decomposition				
RIF composition	0.039***	0.000	0.033***	0.004***
	(0.002)	(0.000)	(0.002)	(0.000)
RIF specification error	–0.010**	0.000	–0.005	–0.001***
	(0.004)	(0.000)	(0.004)	(0.000)
RIF earnings structure	–0.078***	–0.030***	–0.073***	–0.032***
	(0.005)	(0.001)	(0.005)	(0.001)
RIF reweighting error	0.005*	–0.000***	0.001	–0.000**
	(0.003)	(0.000)	(0.003)	(0.000)
RIF detailed decomposition				
RIF composition				
RTI	–0.001	–0.000	0.002**	0.004***
	(0.001)	(0.000)	(0.001)	(0.000)
Age	0.004***	0.000**	0.003***	0.000
	(0.001)	(0.000)	(0.001)	(0.000)
Sex	–0.000	–0.000*	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Education	0.001	–0.000	–0.000	0.000*
	(0.001)	(0.000)	(0.001)	(0.000)
Public	0.045***	0.000***	0.041***	0.000
	(0.002)	(0.000)	(0.002)	(0.000)
Industry	–0.009***	–0.000	–0.012***	–0.000
	(0.001)	(0.000)	(0.001)	(0.000)
RIF earnings structure				
RTI	–0.026***	–0.002	–0.011***	0.002*
	(0.008)	(0.002)	(0.004)	(0.001)
Age	–0.045**	–0.019***	–0.037*	–0.011**
	(0.023)	(0.005)	(0.022)	(0.005)
Sex	–0.007	0.027***	0.000	0.037***
	(0.027)	(0.003)	(0.022)	(0.003)
Education	0.017	0.008*	0.052**	0.020***
	(0.031)	(0.004)	(0.024)	(0.005)
Public	–0.067*	0.016**	–0.049	–0.005
	(0.038)	(0.007)	(0.033)	(0.008)
Industry	0.003	0.037***	0.007	0.040***
	(0.011)	(0.003)	(0.011)	(0.003)
Intercept	0.047	–0.097***	–0.034	–0.115***
	(0.088)	(0.014)	(0.069)	(0.014)

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

Source: authors' illustration based on ENPE data.

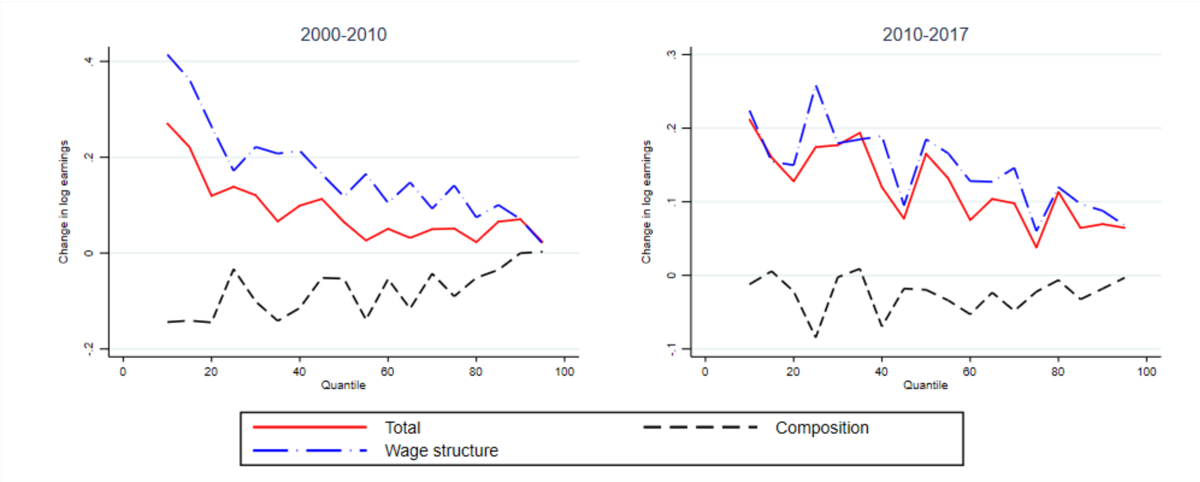
Table 10: RIF decomposition of changes in the q50/q10 and q90/q50 ratios (country-specific RTI)

	q50/q10		q90/q50	
	2000–10	2010–17	2000–10	2010–17
Final F	0.570***	0.523***	0.839***	0.736***
	(0.005)	(0.010)	(0.004)	(0.013)
Initial I	0.834***	0.570***	0.840***	0.839***
	(0.011)	(0.005)	(0.008)	(0.004)
Total change (F–I)	–0.264***	–0.046***	–0.001	–0.103***
	(0.012)	(0.011)	(0.008)	(0.013)
Reweighting decomposition				
Counterfactual C	0.918***	0.583***	0.915***	0.825***
	(0.044)	(0.005)	(0.022)	(0.006)
Total composition (C–I)	0.084**	0.013**	0.075***	–0.014**
	(0.042)	(0.006)	(0.022)	(0.006)
Total earnings structure (F–C)	–0.348***	–0.059***	–0.076***	–0.090***
	(0.045)	(0.011)	(0.022)	(0.014)
RIF aggregate decomposition				
RIF composition	0.102***	–0.010***	0.121***	–0.005***
	(0.013)	(0.002)	(0.007)	(0.001)
RIF specification error	–0.018	0.023***	–0.045**	–0.009*
	(0.039)	(0.006)	(0.022)	(0.005)
RIF earnings structure	–0.368***	–0.058***	–0.086***	–0.090***
	(0.039)	(0.011)	(0.017)	(0.014)
RIF reweighting error	0.020	–0.001***	0.010	0.001***
	(0.016)	(0.000)	(0.009)	(0.000)
RIF detailed decomposition				
RIF composition				
RTI	–0.006*	–0.001	–0.005	–0.001
	(0.004)	(0.001)	(0.003)	(0.001)
Age	0.024***	–0.002***	0.002	–0.004***
	(0.004)	(0.001)	(0.002)	(0.001)
Sex	–0.001	–0.001	–0.001	–0.000*
	(0.001)	(0.000)	(0.001)	(0.000)
Education	–0.005*	–0.008***	0.008***	0.001***
	(0.003)	(0.001)	(0.002)	(0.000)
Public	0.089***	0.002***	0.155***	0.000**
	(0.012)	(0.000)	(0.007)	(0.000)
Industry	0.002	0.000	–0.039***	–0.001
	(0.005)	(0.000)	(0.003)	(0.000)
RIF earnings structure				
RTI	0.019	0.017**	0.003	–0.080***
	(0.036)	(0.007)	(0.024)	(0.010)
Age	–0.240**	0.012	–0.205**	0.154***
	(0.104)	(0.023)	(0.087)	(0.022)
Sex	0.041	–0.260***	0.163**	0.132***
	(0.121)	(0.018)	(0.075)	(0.017)
Education	–0.154	0.320***	0.037	0.071***
	(0.142)	(0.026)	(0.083)	(0.023)
Public	–0.102	0.102***	–0.267	–0.108***
	(0.205)	(0.027)	(0.167)	(0.027)
Industry	0.182***	–0.079***	–0.027	0.090***
	(0.068)	(0.015)	(0.033)	(0.010)
Intercept	–0.115	–0.169***	0.211	–0.348***
	(0.259)	(0.060)	(0.287)	(0.051)

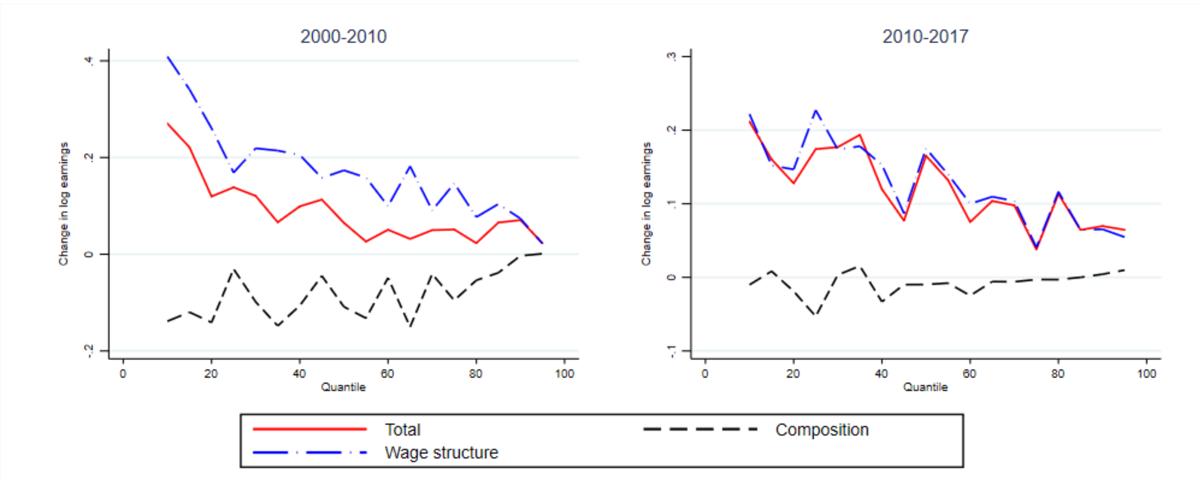
Note: standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: authors' illustration based on ENPE data.

Figure 11: RIF decomposition of total earnings change into wage structure and composition effects
(a) Country-specific RTI

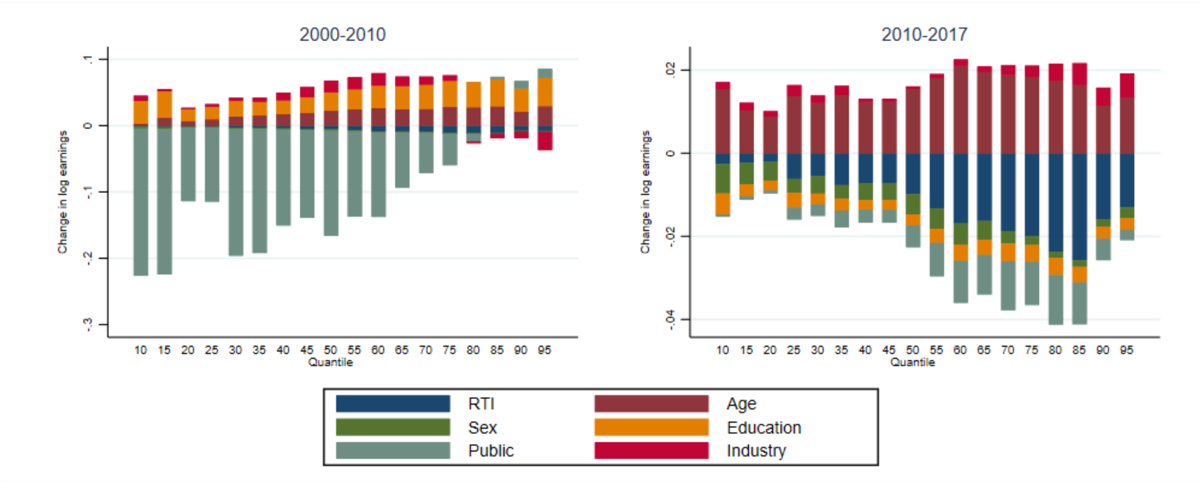


(b) O*NET RTI

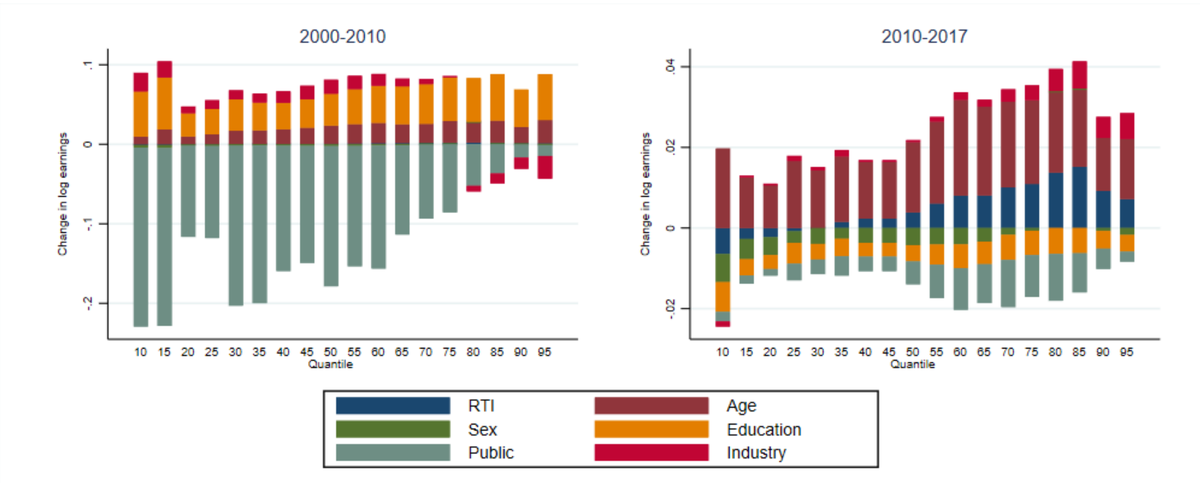


Source: authors' illustration based on ENPE data.

Figure 12: Detailed RIF decomposition of determinants of earnings changes: composition effects
(a) Country-specific RTI

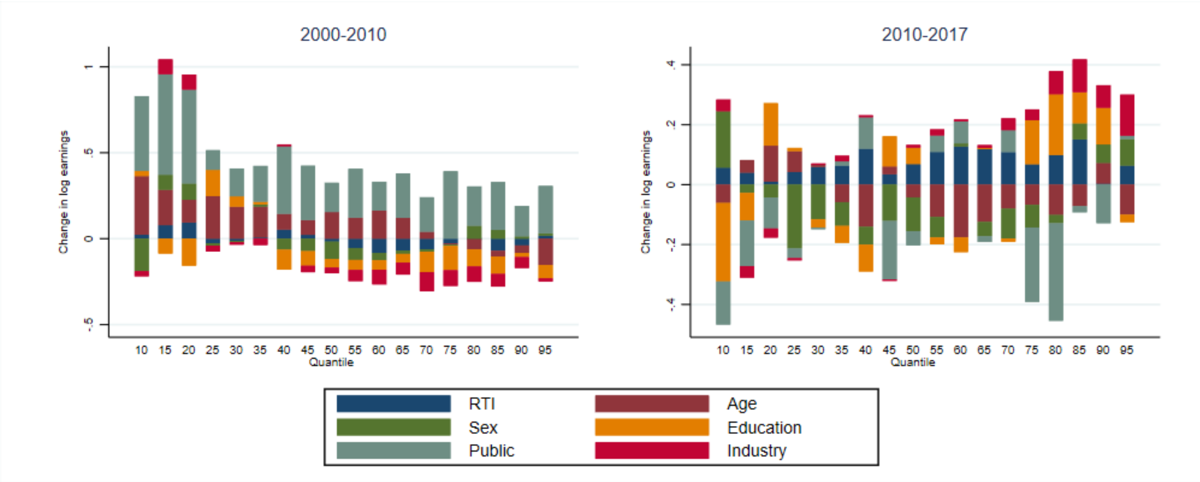


(b) O*NET RTI

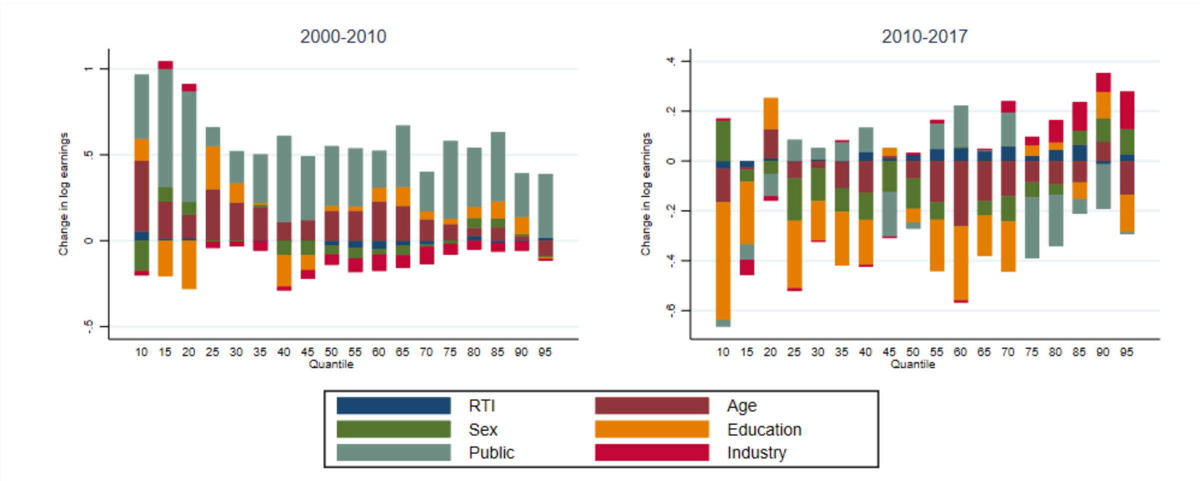


Source: authors' illustration based on ENPE data.

Figure 13: Detailed RIF decomposition of determinants of earnings changes: wage structure effects
(a) Country-specific RTI



(b) O*NET RTI



Source: authors' illustration based on ENPE data.

6 Conclusion

In this study we investigated the links between inequality and the changing nature of jobs in a revolution context. We also study the determinants of inequality variation including the Tunisian Revolution and, in particular, its impact on public hiring and wage policies.

Earnings inequality decreased significantly during the period of investigation in Tunisia due mainly to decreasing education premia. This evolution of education premia is similar in all MENA countries as they are characterized by an excess supply of tertiary-educated job seekers due to a pattern of specialization based on low- and medium-skill labour. The employment and wage policies in the public sector since the Revolution also played a role in reducing inequality. Moreover, wage polarization is highlighted, but unlike developed countries, Tunisian polarization seems to have been mainly led by an increase in the lowest wages similarly to what has been observed in China.

In terms of jobs, the share of high-skilled labour in total employment increased until 2010, but decreased after the Revolution, mainly for self-employed, whose share of total employment increased. The main explanation lies in the increase of the share of agriculture and the share of unskilled government workers under pressure following the Revolution.

Despite a significant reduction in clerical positions, the aggregate routine task index increases over the whole examined period, which was probably due to the expanding demand for labourers and machine operators in manufacturing and construction in the first period, and the public recruitment policy together with the increase in agricultural demand in the second period.

The Shapley decomposition showed that half of the earnings inequality resulted from the between-occupations differences, most of which could be attributed to the routine task index of jobs, while changes in average occupational earnings are the main driver of the changes in inequality over time.

Finally, our RIF decomposition of earnings inequality changes suggests that public sector, education, and occupations were the three factors that explain most of the differential changes at the bottom and top of the distribution.

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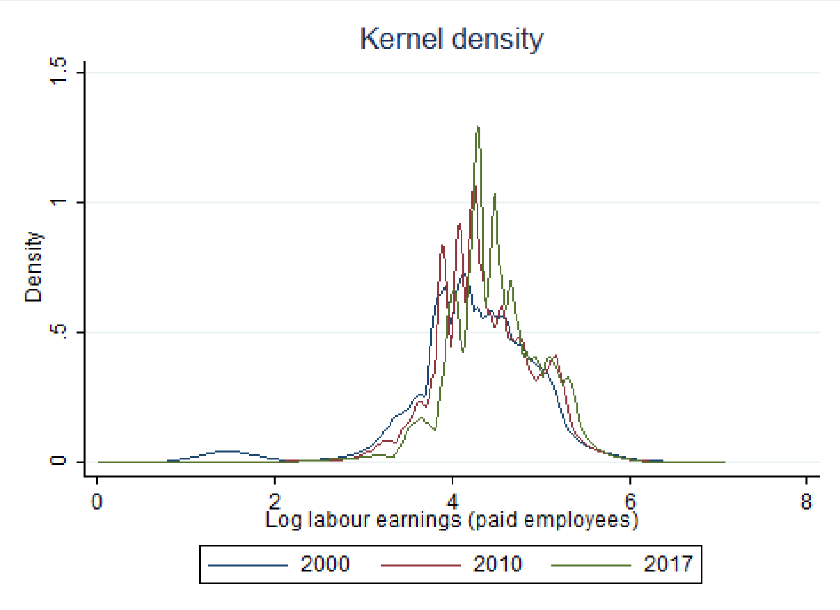
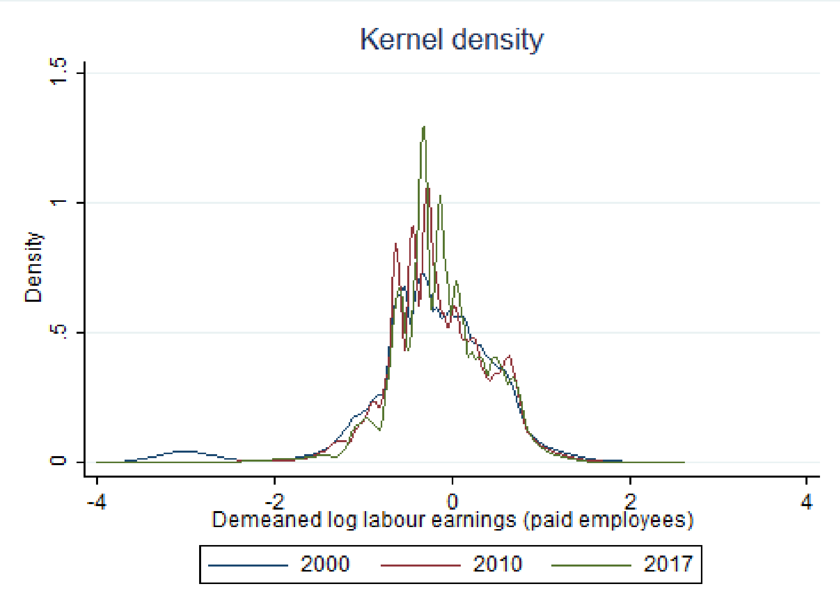
Appendix

A1 Changes in job distribution and earnings inequality

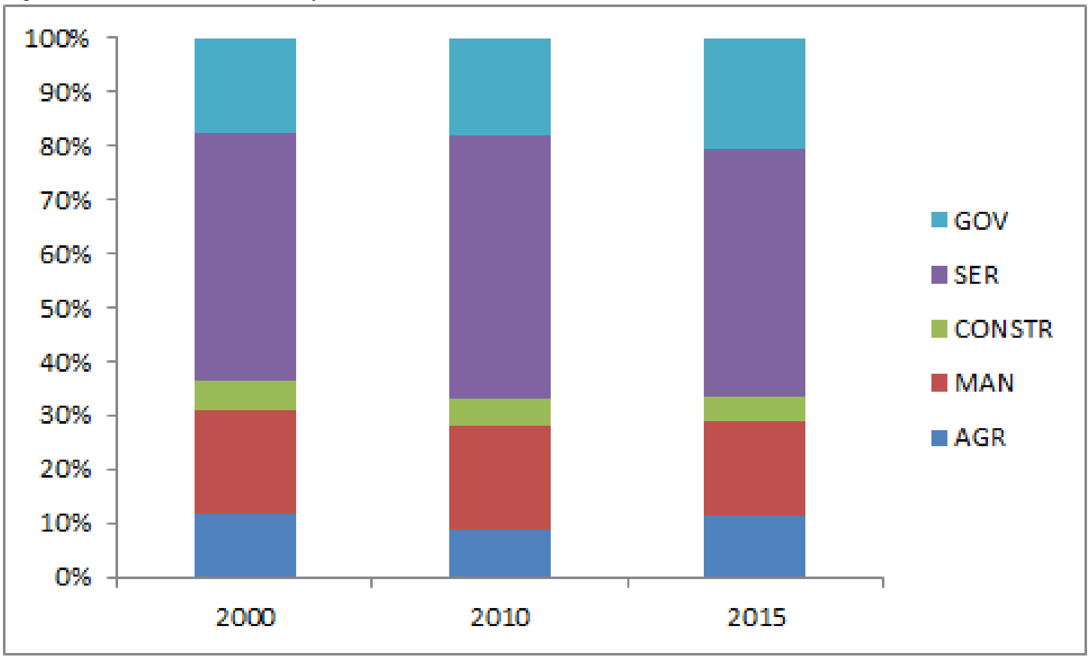
Figure A1: Adaptive kernel densities





Source: authors' illustration based on ENPE data.

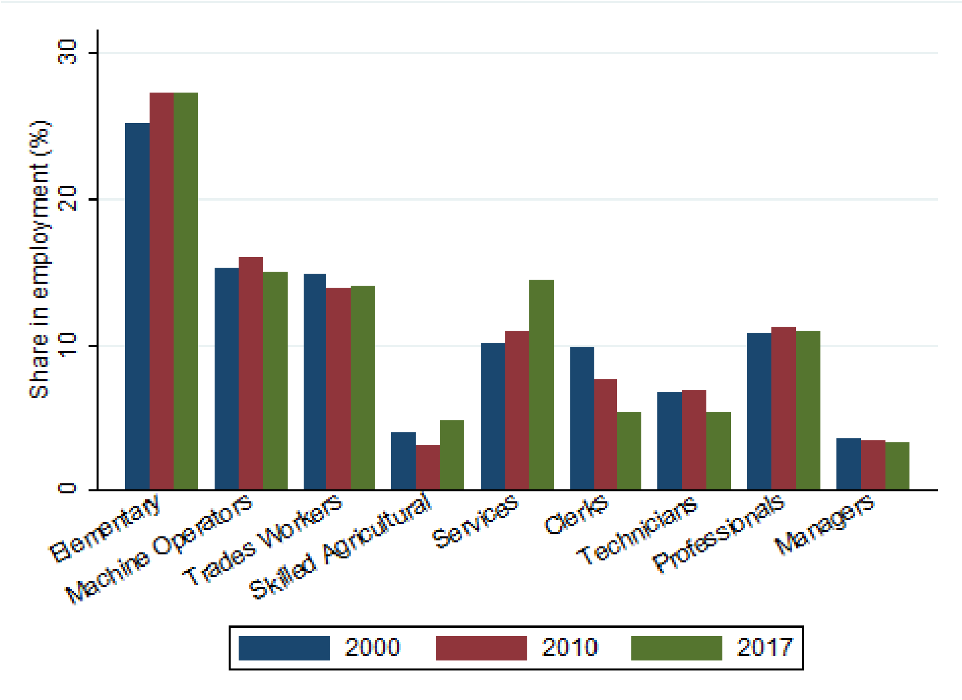
Figure A2: Distribution of GDP by sector 2000–15



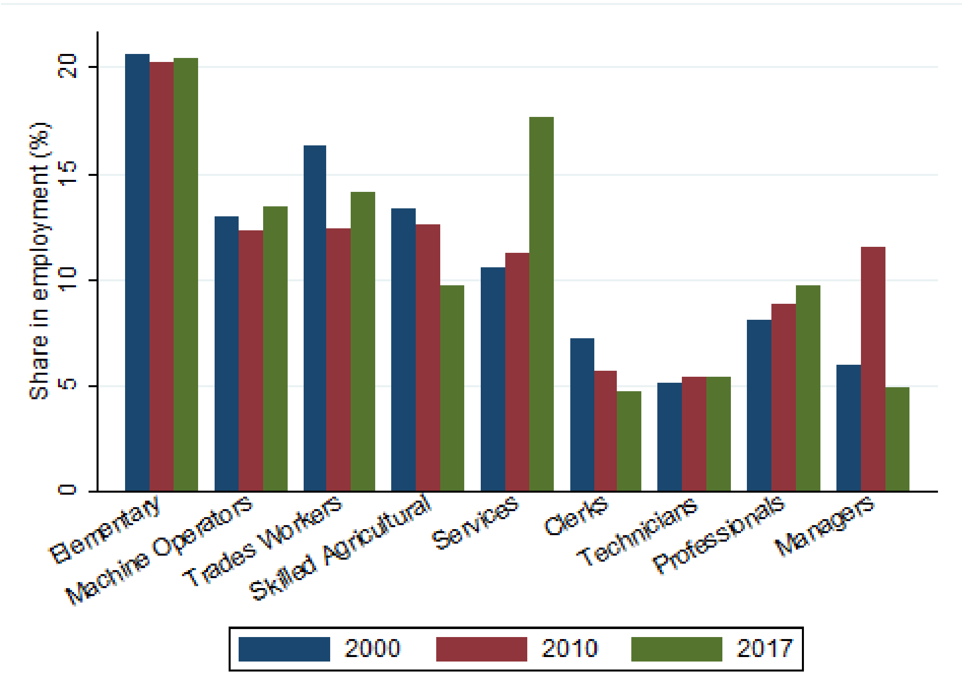
Source: authors' illustration based on ENPE data.

Figure A3: Employment shares by occupational groups at the one-digit level

(a) Paid employees



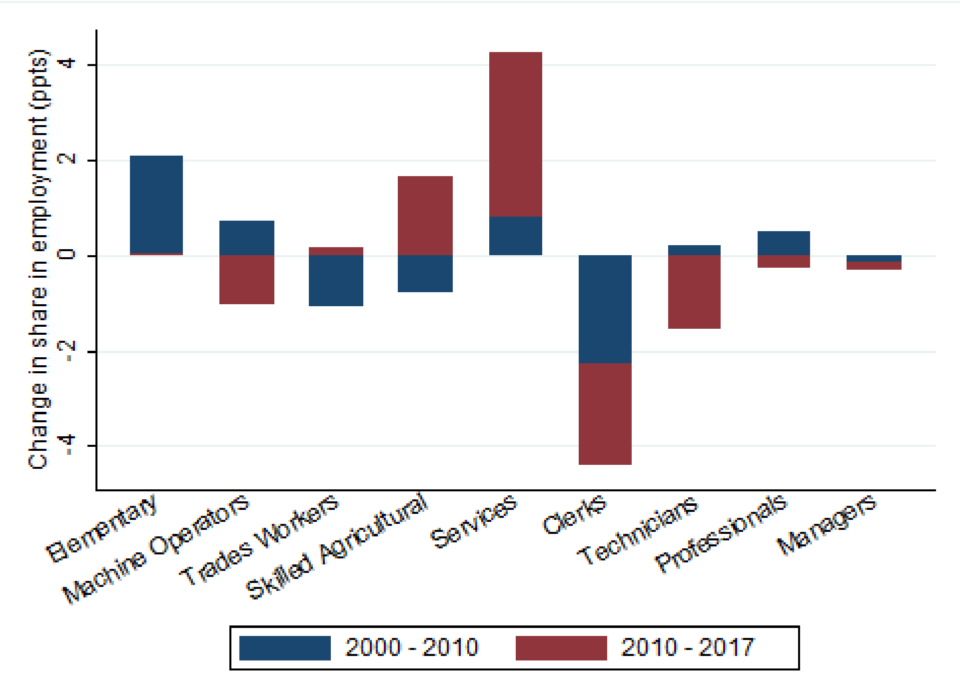
(b) All workers



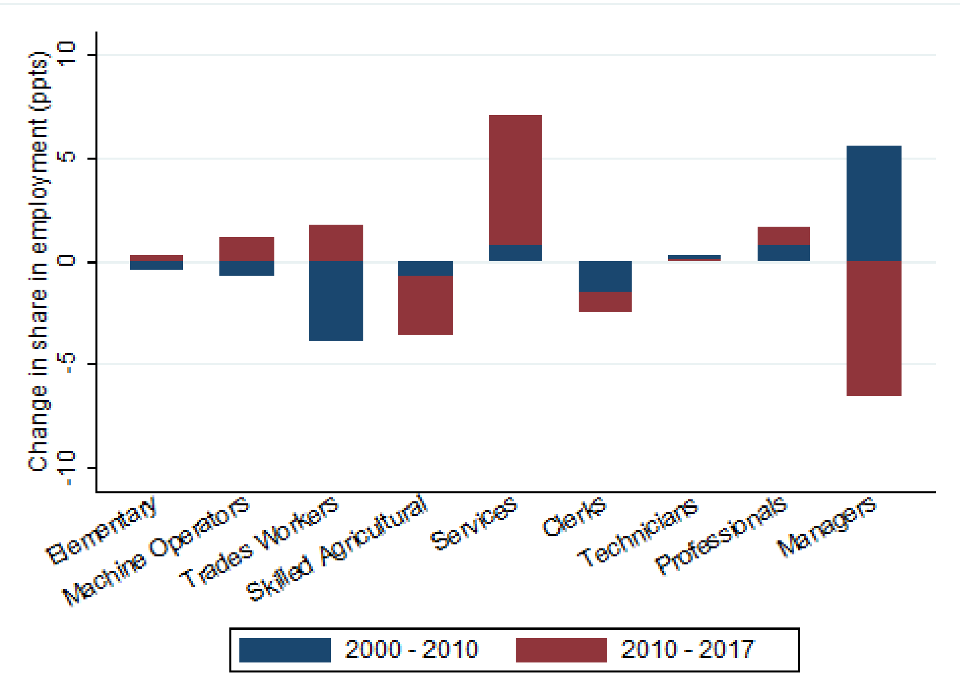
Source: authors' illustration based on ENPE data.

Figure A4: Changes in employment shares by occupational groups at the one-digit level

(a) Paid employees



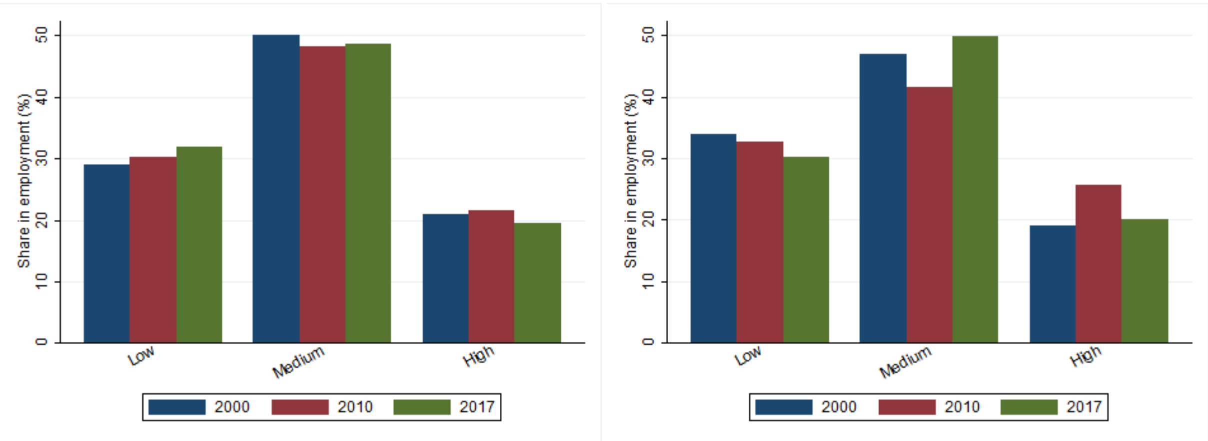
(b) All workers



Source: authors' illustration based on ENPE data.

Figure A5: Employment shares by skill levels

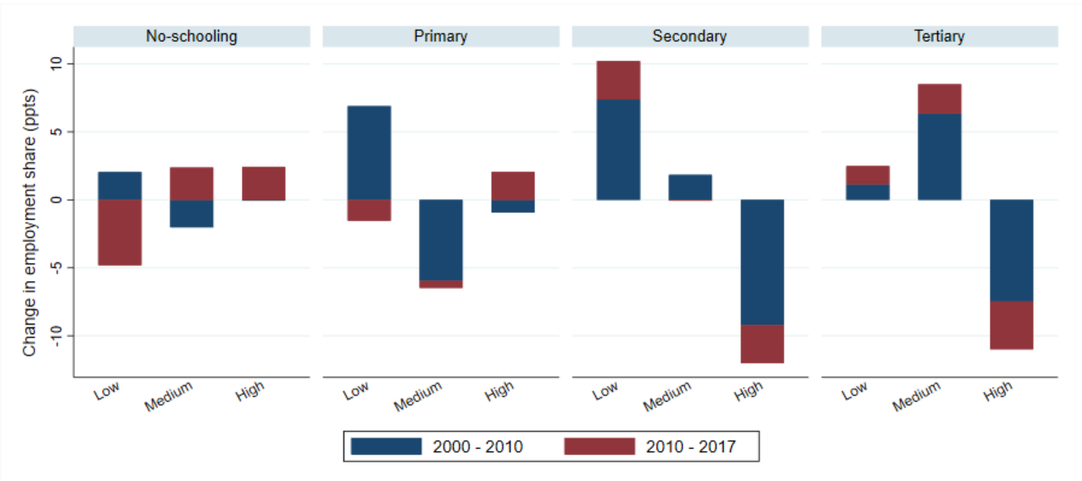
(a) Paid employees (b) All workers



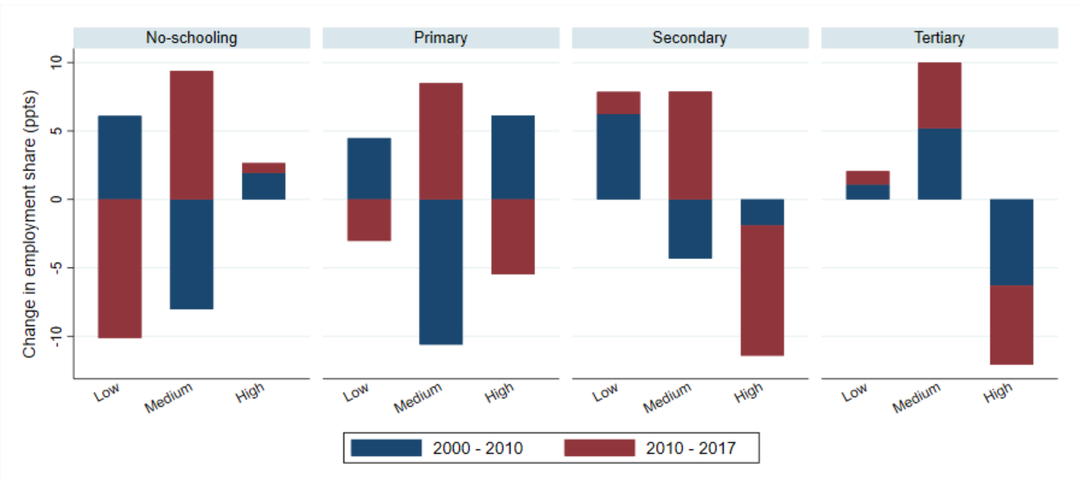
Source: authors' illustration based on ENPE data.

Figure A6: Changes in employment shares by education levels

(a) Paid employees

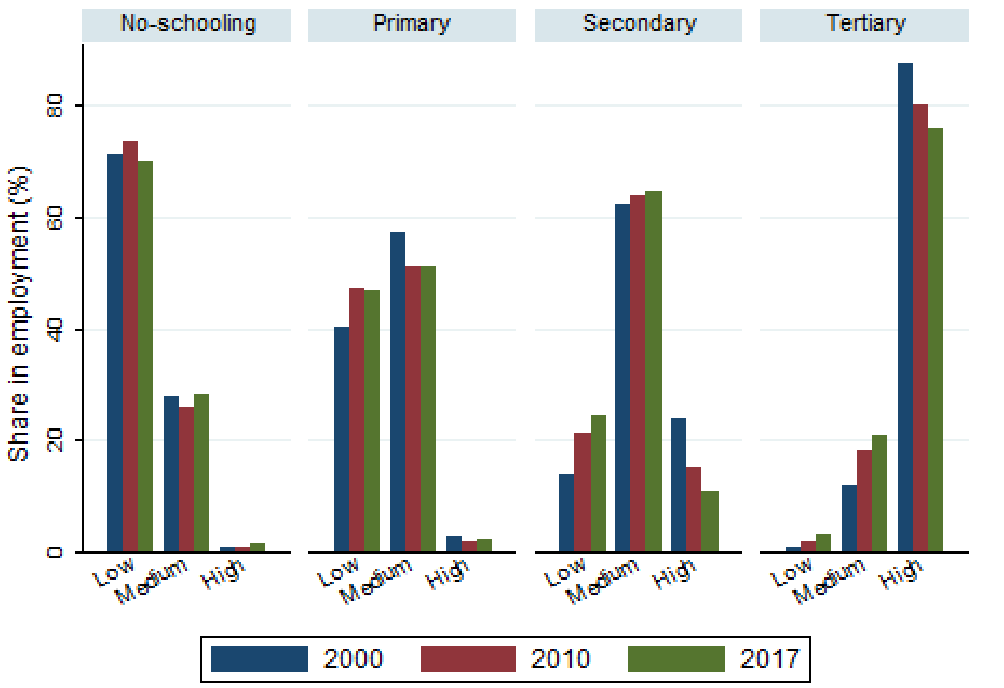


(b) All workers



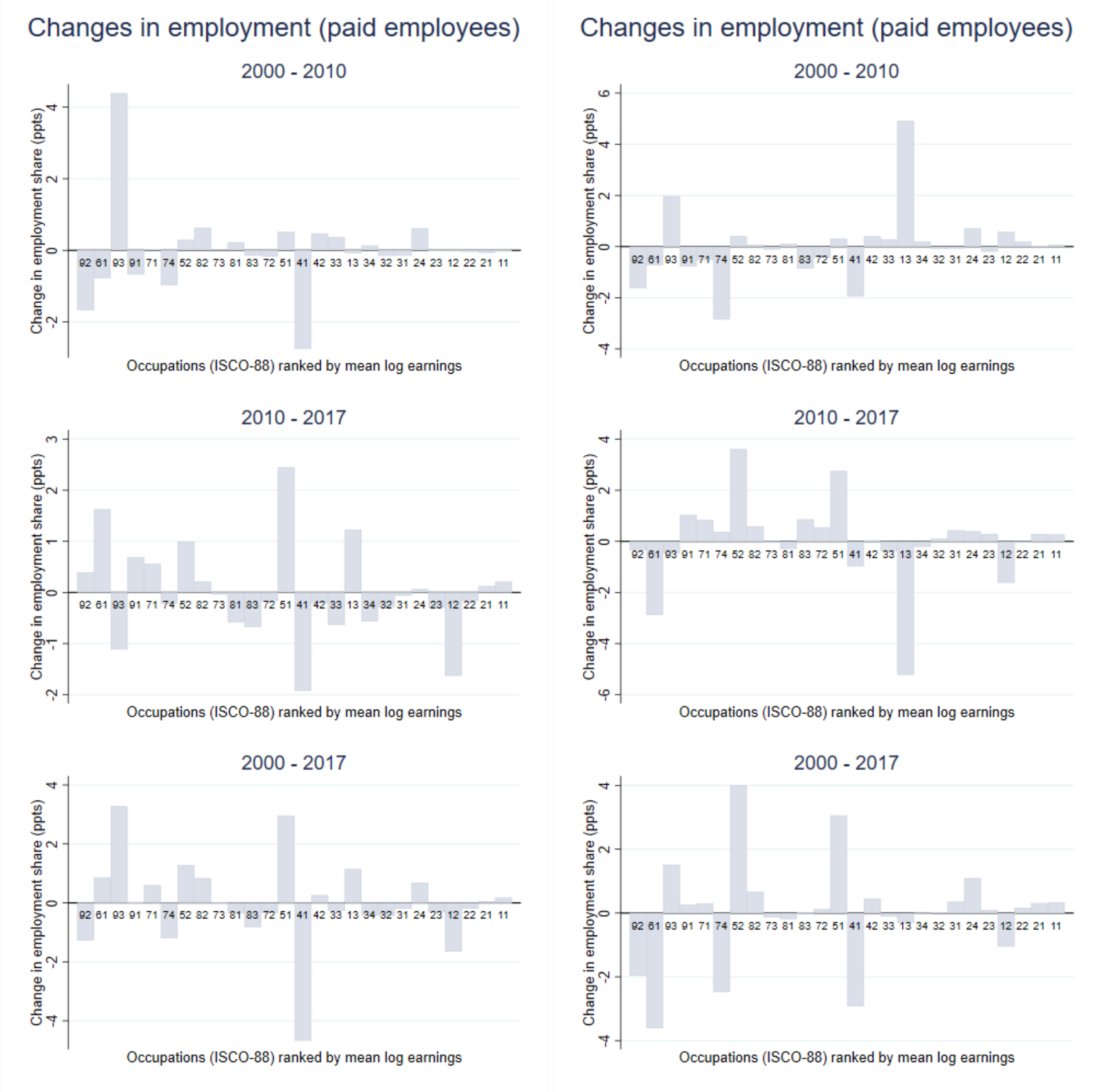
Source: authors' illustration based on ENPE data.

Figure A7: Employment shares by education levels: All workers



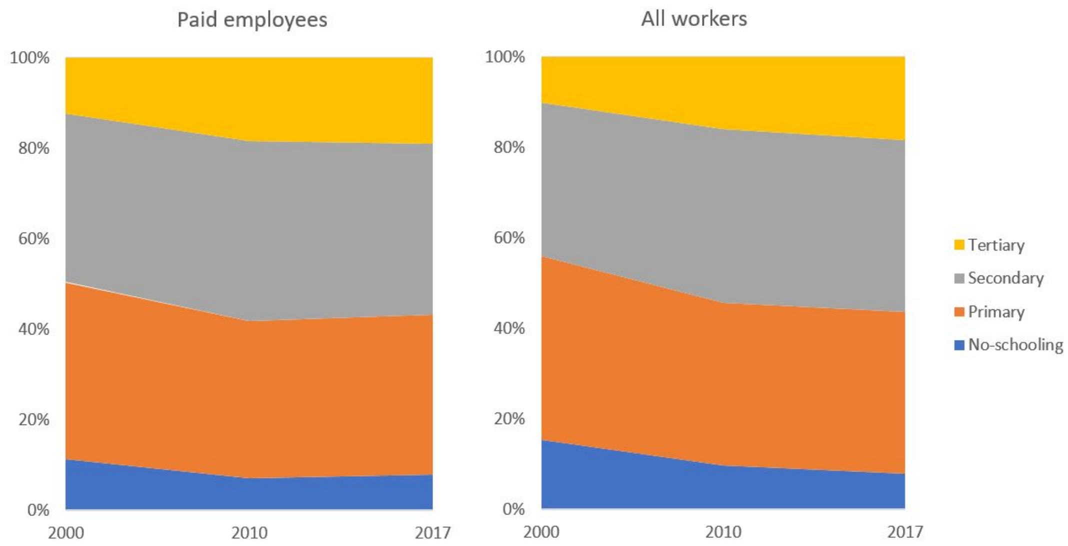
Source: authors' illustration based on ENPE data.

Figure A8: Smooth changes in employment share by occupational groups at the two-digit level



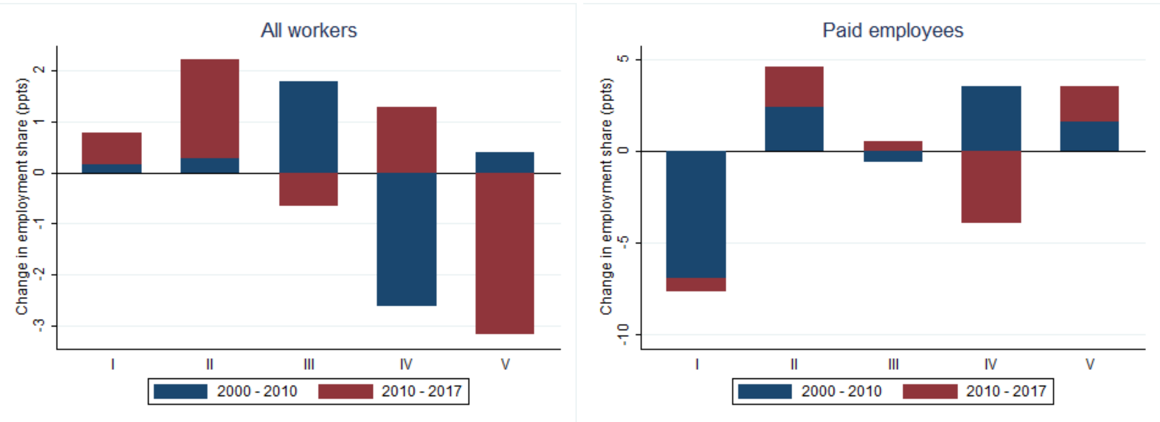
Source: authors' illustration based on ENPE data.

Figure A9: Employment distribution by education levels



Source: authors' illustration based on ENPE data.

Figure A10: Changes in employment shares by skill quintiles



Source: authors' illustration based on ENPE data.

Figure A11: Changes in employment shares by skill quintiles and sectors

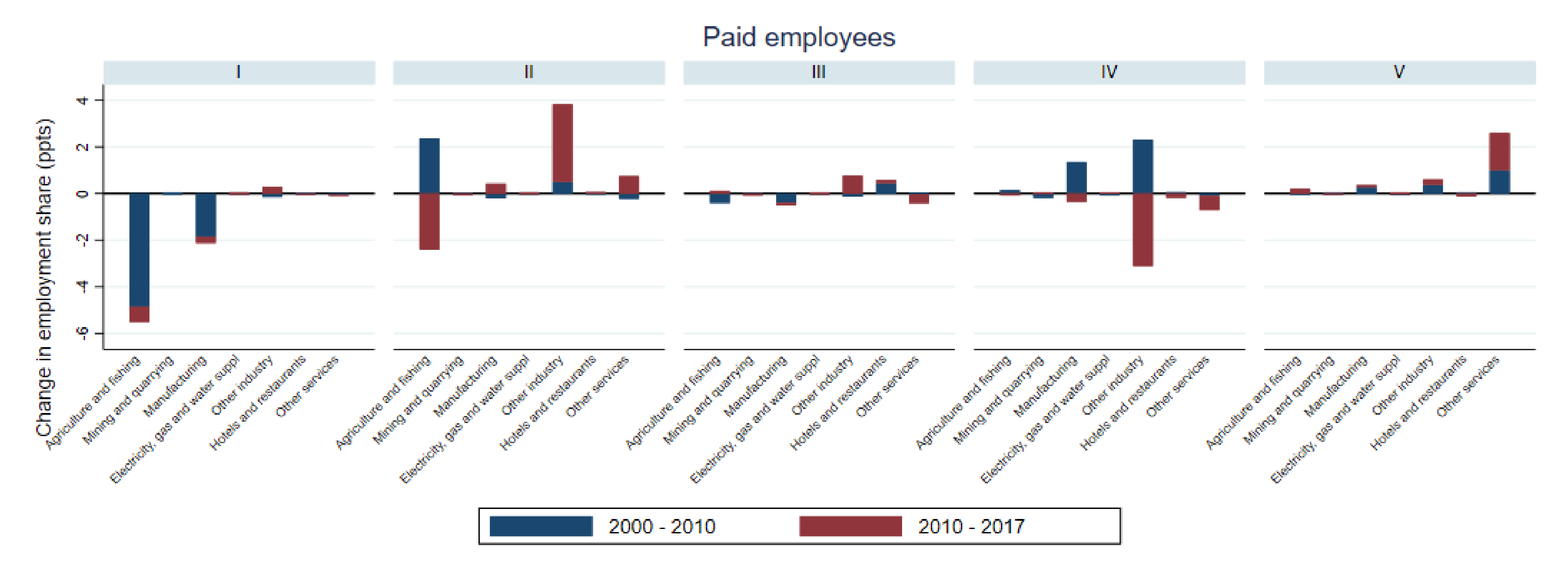
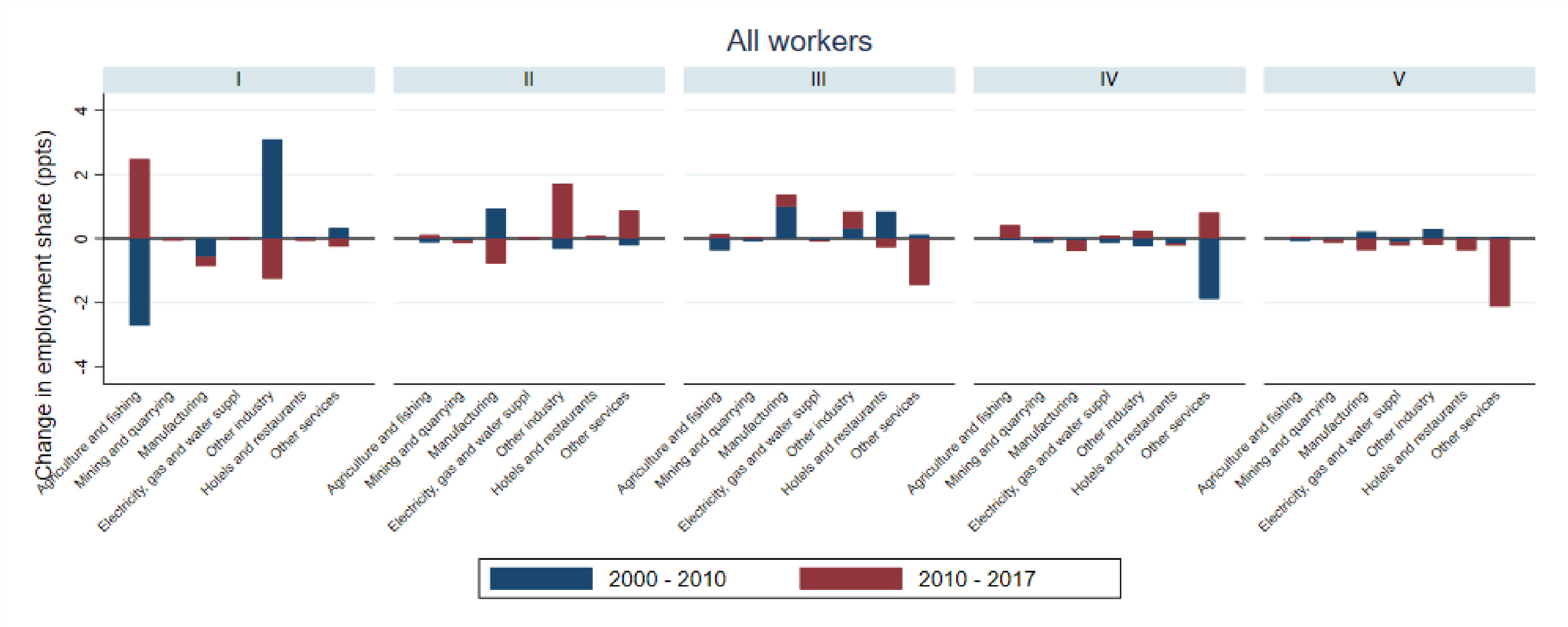


Figure A11 (continued)



Source: authors' illustration based on ENPE data.

Table A1: Employment shares by three-digit occupational categories for ISCO-88 categories 3, 4, and 5 (%)

Occupation		2000	2010	2017
311	Physical and engineering science technicians	1.22	1.09	0.78
312	Computer associate professionals	0.10	0.25	0.14
313	Optical and electronic equipment operators	0.25	0.18	0.18
314	Ship and aircraft controllers and technicians	0.18	0.04	0.02
315	Safety and quality inspectors	0.14	0.19	0.57
321	Life science technicians and related associate professional	0.31	0.14	0.22
322	Health associate professionals (except nursing)	0.30	0.55	0.42
323	Nursing and midwifery associate professionals	1.56	1.32	1.09
333	Special education teaching associate professionals		0.05	0.06
334	Other teaching associate professionals	0.55	0.86	0.22
341	Finance and sales associate professionals	0.35	0.33	0.44
342	Business services agents and trade brokers	0.25	0.10	0.10
343	Administrative associate professionals	0.77	1.26	0.80
344	Customs, tax, and related government associate professionals	0.25	0.10	0.07
346	Social work associate professionals	0.16	0.06	0.03
347	Artistic, entertainment, and sports associate professionals	0.30	0.36	0.22
411	Secretaries and keyboard-operating clerks	4.89	3.24	1.90
412	Numerical clerks	1.17	0.50	0.17
413	Material-recording and transport clerks	1.68	1.62	0.76
414	Library, mail, and related clerk	0.58	0.26	0.28
419	Other office clerks	0.16	0.10	0.69
421	Cashiers, tellers, and related clerks	0.57	0.70	0.45
422	Client information clerks	0.76	1.09	1.13
511	Travel attendants and related workers	0.25	0.23	0.15
512	Housekeeping and restaurant services workers	2.62	3.20	3.18
513	Personal care and related workers	0.22	0.36	0.22
514	Other personal services workers	0.60	0.70	0.56
516	Protective services workers	3.64	3.34	6.19
522	Shop salespersons and demonstrators	2.31	2.84	3.75
523	Stall and market salespersons	0.46	0.23	0.30

Source: authors' illustration based on ENPE data.

Table A2: Employment share changes by industries (%)

Industry		2000–10	2010–17
1	Agriculture	–33.07	50.61
2	Mining	–30.55	–16.74
3	Manufacturing	7.22	–6.05
4	Utilities	–29.76	–0.72
5	Construction	19.87	–3.16
6	Sales	–1.23	22.40
7	Hospitality	16.87	–13.12
8	Transport and ICT	1.95	–27.03
9	Finance	–39.90	3.25
10	Real estate	51.26	14.04
11	Public administration	–21.03	–3.41
12	Education	3.22	–4.66
13	Health	3.46	7.87
14	Other services	11.81	–24.44
15	Private households	10.10	13.15
16	NGOs	–59.28	–9.10

Source: authors' illustration based on ENPE data.

Table A3: Job and earnings polarization tests, median earnings

	Change in employment share			Change in log median earnings		
	2000–10	2010–17	2000–17	2000–10	2010–17	2000–17
Initial log median earnings	1.266	–1.930	0.243	–0.977**	–1.026**	–1.572***
	(1.546)	(2.218)	(2.435)	(0.452)	(0.454)	(0.463)
Sq. initial log median earnings	–0.148	0.184	–0.063	0.099*	0.099*	0.153***
	(0.173)	(0.242)	(0.275)	(0.052)	(0.051)	(0.053)
Constant	–2.744	4.795	–0.028	2.469**	2.709***	4.129***
	(3.448)	(5.025)	(5.337)	(0.972)	(0.999)	(0.989)
Observations	103	101	101	103	101	101
R-squared	0.013	0.059	0.065	0.210	0.235	0.446
Adj. R-squared	–0.006	0.040	0.046	0.194	0.219	0.434
F-test	0.631	0.074	0.134	0.000	0.000	0.000

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

Source: authors' illustration based on ENPE data.

Table A4: Job and earnings polarization tests, including imputed earnings for self-employed

	Change in employment share			Change in log median earnings		
	2000–10	2010–17	2000–17	2000–10	2010–17	2000–17
Initial log mean earnings	0.253	0.834	1.163	–2.004***	–1.099*	–1.939***
	(1.187)	(2.676)	(1.579)	(0.318)	(0.570)	(0.334)
Sq. initial log mean earnings	–0.018	–0.137	–0.156	0.206***	0.091	0.175***
	(0.137)	(0.299)	(0.186)	(0.038)	(0.065)	(0.041)
Constant	–0.832	–1.105	–2.243	4.871***	3.146**	5.261***
	(2.567)	(5.934)	(3.297)	(0.646)	(1.249)	(0.674)
Observations	99	99	99	99	99	99
R-squared	0.016	0.136	0.030	0.618	0.647	0.792
Adj. R-squared	–0.004	0.118	0.010	0.610	0.640	0.788
F-test	0.758	0.018	0.324	0.000	0.000	0.000

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

Source: authors' illustration based on ENPE data.

Table A5: Job and earnings polarization tests, excluding agriculture

	Change in employment share			Change in log median earnings		
	2000–10	2010–17	2000–17	2000–10	2010–17	2000–17
Initial log mean earnings	–2.076	–0.340	–2.710	–2.332***	–1.561**	–3.498***
	(1.920)	(3.354)	(3.274)	(0.625)	(0.780)	(0.992)
Sq. initial log mean earnings	0.216	0.016	0.266	0.241***	0.148*	0.350***
	(0.215)	(0.367)	(0.369)	(0.068)	(0.084)	(0.109)
Constant	4.822	1.074	6.488	5.632***	4.098**	8.707***
	(4.265)	(7.590)	(7.174)	(1.443)	(1.804)	(2.238)
Observations	103	100	100	103	100	100
R-squared	0.059	0.024	0.071	0.382	0.421	0.638
Adj. R-squared	0.040	0.004	0.0517	0.369	0.409	0.631
F-test	0.252	0.312	0.0746	0.000	0.000	0.000

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

Source: authors' illustration based on ENPE data.

Table A6: Job and earnings polarization tests, excluding public sector

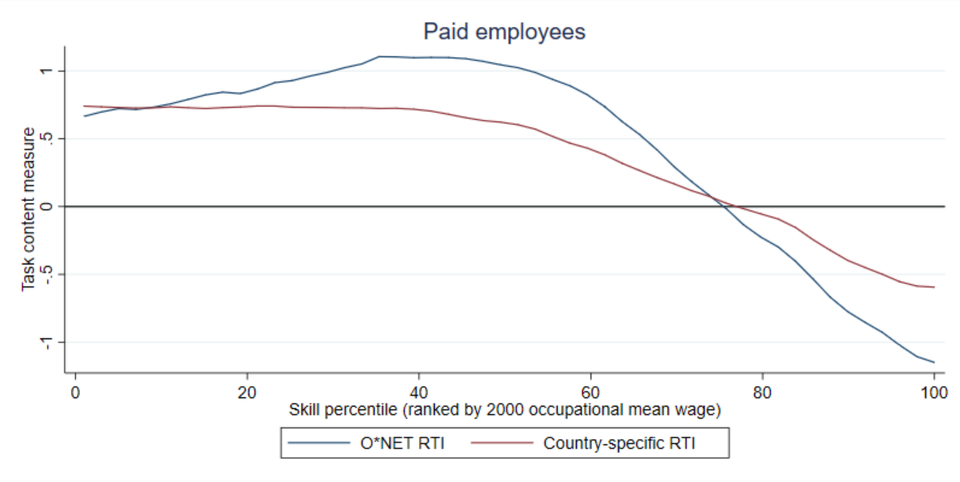
	Change in employment share			Change in log median earnings		
	2000–10	2010–17	2000–17	2000–10	2010–17	2000–17
Initial log mean earnings	2.756***	–1.345	3.066**	–1.936***	0.171	–1.500***
	(0.676)	(2.565)	(1.253)	(0.343)	(0.565)	(0.374)
Sq. initial log mean earnings	–0.331***	0.108	–0.409**	0.192***	–0.053	0.114**
	(0.086)	(0.290)	(0.159)	(0.043)	(0.065)	(0.047)
Constant	–5.751***	3.632	–5.808**	4.832***	0.361	4.484***
	(1.331)	(5.640)	(2.451)	(0.654)	(1.224)	(0.724)
Observations	99	99	96	99	99	96
R-squared	0.088	0.073	0.122	0.590	0.454	0.737
Adj. R-squared	0.069	0.054	0.103	0.581	0.443	0.732
F-test	0.000	0.030	0.021	0.000	0.000	0.000

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

Source: authors' illustration based on ENPE data.

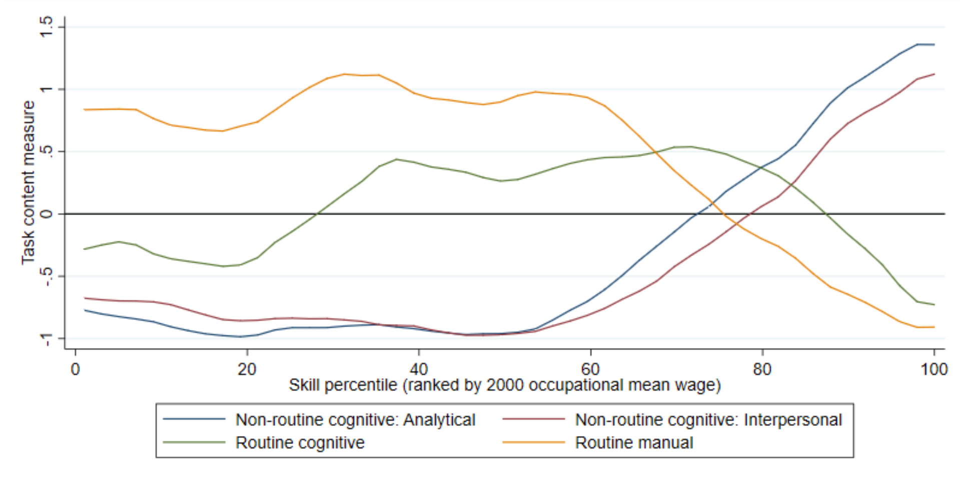
A2 Task-based analysis

Figure A12: Task content by measures



Source: authors' illustration based on ENPE data.

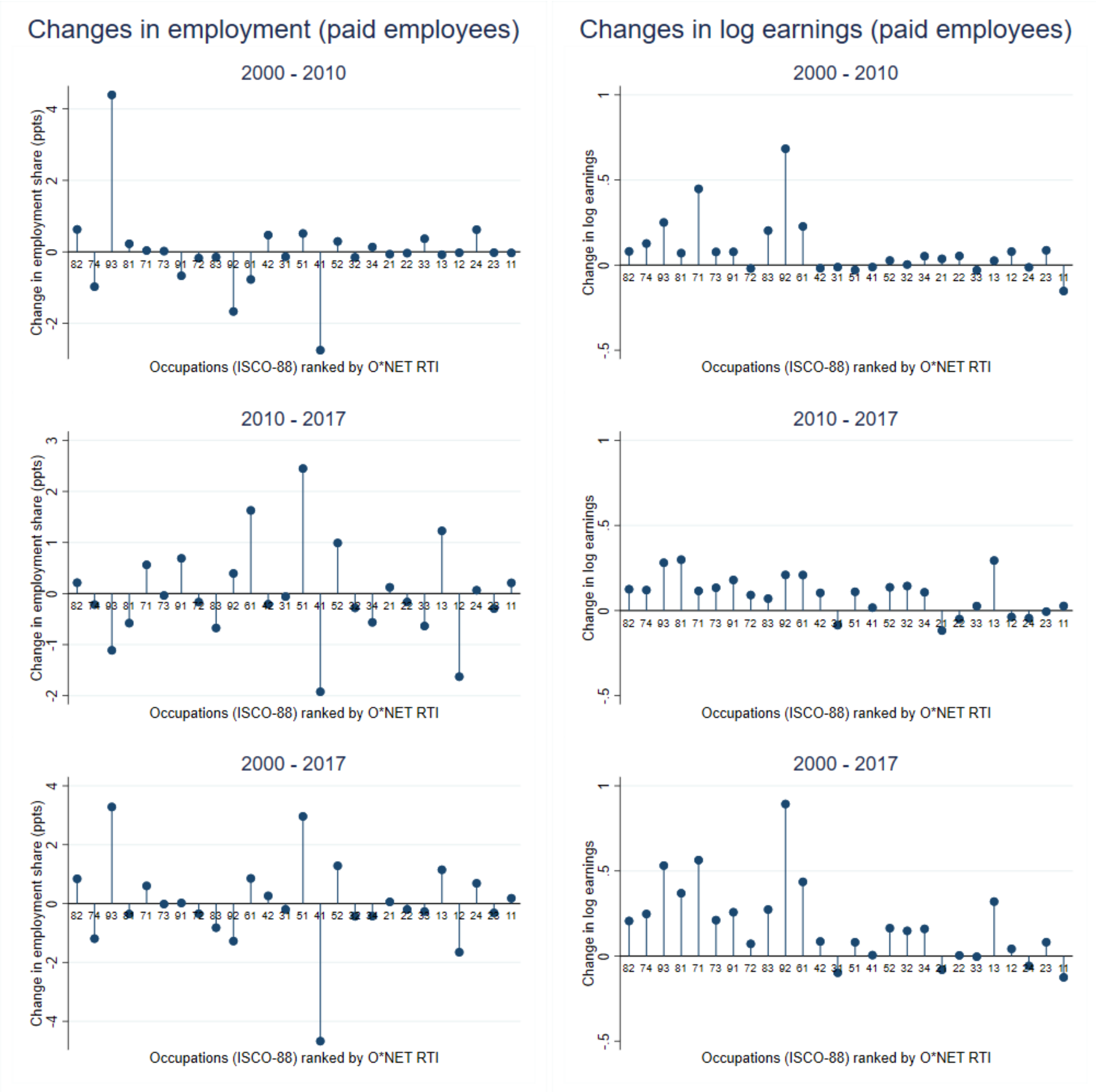
Figure A13: O*NET RTI task content by components



Source: authors' illustration based on ENPE data.

Figure A14: Change in log earnings and employment share of occupations ranked by O*NET RTI (paid employees)

(a) Employment share (b) Log earnings



Source: authors' illustration based on ENPE data.

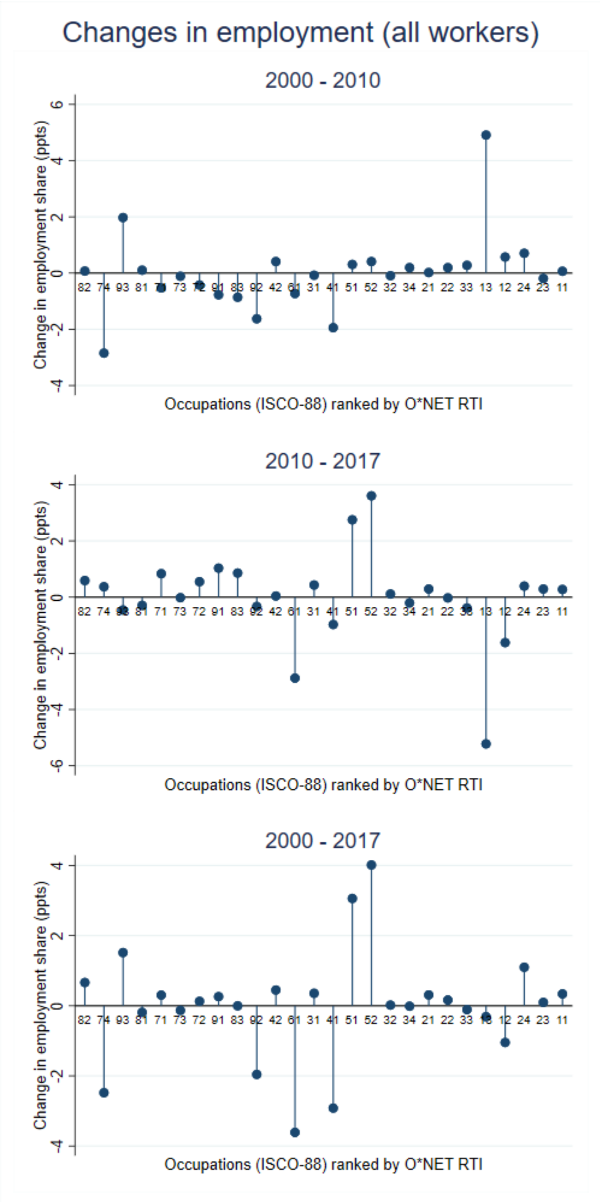
Figure A15: Change in log earnings and employment share of occupations ranked by country-specific RTI (paid employees)

(a) Employment share
(b) Log earnings

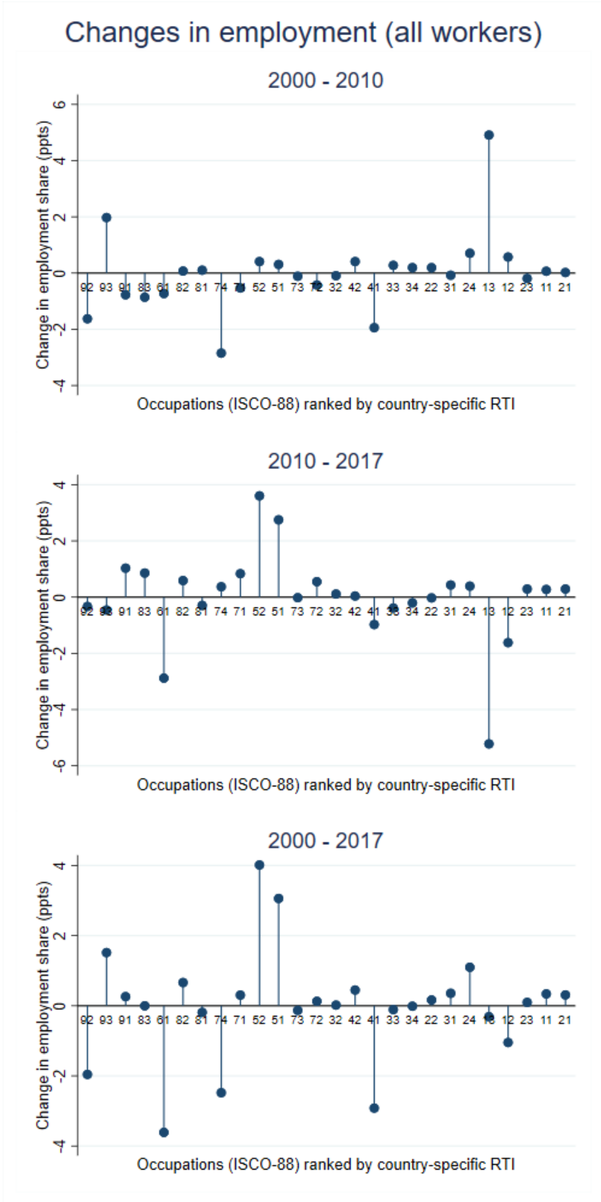
Source: authors' illustration based on ENPE data.

Figure A16: Changes in employment share by occupational groups at the two-digit level, ranked by RTI (all workers)

(a) O*NET RTI



(b) Country-specific RTI



Source: authors' illustration based on ENPE data.

A3 Determinants of changes in earnings inequality

Table A7: Baseline composition: RIF decomposition of changes in Gini

	Country-specific RTI		O*NET RTI	
	2000–10	2020–17	2000-10	2020-17
Final F	0.316***	0.286***	0.316***	0.286***
	(0.001)	(0.001)	(0.001)	(0.001)
Initial I	0.360***	0.316***	0.360***	0.316***
	(0.002)	(0.001)	(0.002)	(0.001)
Total change (F–I)	–0.044***	–0.030***	–0.044***	–0.030***
	(0.002)	(0.001)	(0.002)	(0.001)
Reweighting decomposition				
Counterfactual C	0.389***	0.316***	0.388***	0.319***
	(0.006)	(0.001)	(0.005)	(0.001)
Total composition (C–I)	0.029***	0.000	0.028***	0.003***
	(0.005)	(0.000)	(0.004)	(0.001)
Total earnings structure (F–C)	–0.073***	–0.030***	–0.072***	–0.032***
	(0.006)	(0.001)	(0.005)	(0.001)
RIF aggregate decomposition				
RIF composition	–0.003***	–0.000	–0.005***	0.003***
	(0.001)	(0.000)	(0.001)	(0.000)
RIF specification error	0.033***	0.001	0.033***	–0.000
	(0.005)	(0.000)	(0.004)	(0.000)
RIF earnings structure	–0.072***	–0.030***	–0.067***	–0.032***
	(0.006)	(0.001)	(0.005)	(0.001)
RIF reweighting error	–0.001	–0.000***	–0.005***	–0.000***
	(0.001)	(0.000)	(0.001)	(0.000)
RIF detailed decomposition				
RIF composition				
RTI	–0.001	–0.000	0.002**	0.003***
	(0.000)	(0.000)	(0.001)	(0.000)
Age	0.001	0.000*	–0.001	–0.000*
	(0.001)	(0.000)	(0.001)	(0.000)
Sex	0.000	–0.000*	–0.000	–0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Education	–0.004***	–0.000**	–0.006***	–0.000*
	(0.001)	(0.000)	(0.001)	(0.000)
Total composition	–0.004	0.000	–0.005	0.003
RIF earnings structure				
RTI	–0.032***	–0.008***	–0.016***	–0.004***
	(0.009)	(0.001)	(0.004)	(0.001)
Age	–0.036*	–0.010**	–0.032*	0.002
	(0.020)	(0.004)	(0.019)	(0.005)
Sex	0.001	0.029***	0.014	0.040***
	(0.026)	(0.003)	(0.020)	(0.003)
Education	0.028	0.016***	0.063***	0.035***
	(0.028)	(0.004)	(0.021)	(0.004)
Intercept	–0.034	–0.057***	–0.095**	–0.105***
	(0.065)	(0.009)	(0.044)	(0.008)
Total earnings structure	–0.073	–0.03	–0.066	–0.032

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

Source: authors' illustration based on ENPE data.

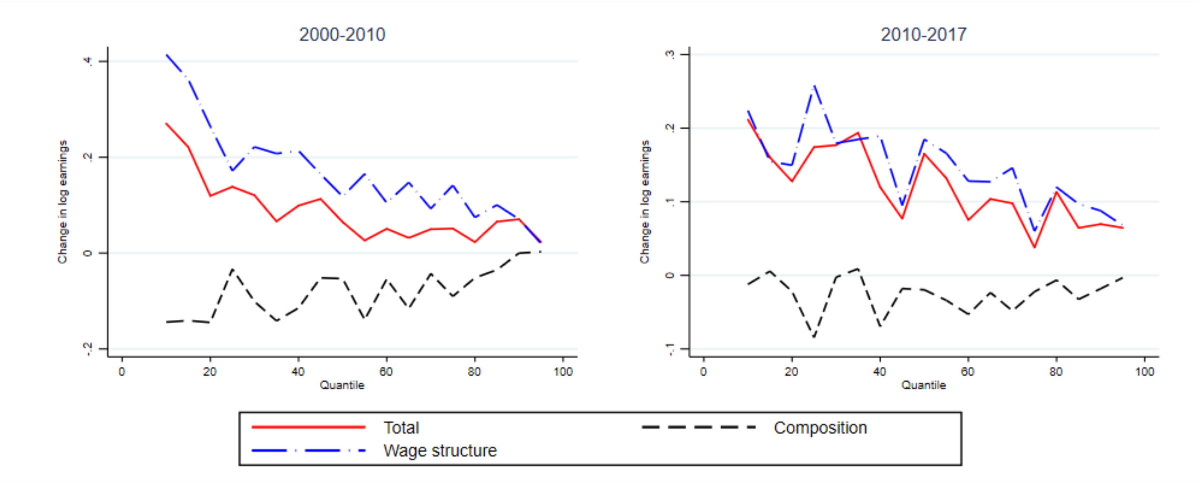
Table A8: Baseline composition: RIF decomposition of changes in the q50/q10 and q90/q50 ratios (country-specific RTI)

	q50/q10		q90/q50	
	2000–10	2010–17	2000–10	2010–17
Final F	0.570***	0.523***	0.839***	0.736***
	(0.005)	(0.010)	(0.004)	(0.013)
Initial I	0.834***	0.570***	0.840***	0.839***
	(0.011)	(0.005)	(0.008)	(0.004)
Total change (F–I)	–0.264***	–0.046***	–0.001	–0.103***
	(0.012)	(0.011)	(0.008)	(0.013)
Reweighting decomposition				
Counterfactual C	0.918***	0.583***	0.915***	0.825***
	(0.044)	(0.005)	(0.022)	(0.006)
Total composition (C–I)	0.084**	0.013**	0.075***	–0.014**
	(0.042)	(0.006)	(0.022)	(0.006)
Total earnings structure (F–C)	–0.348***	–0.059***	–0.076***	–0.090***
	(0.045)	(0.011)	(0.022)	(0.014)
RIF aggregate decomposition				
RIF composition	0.002	–0.004**	–0.019***	–0.007***
	(0.006)	(0.002)	(0.003)	(0.001)
RIF specification error	0.082**	0.017***	0.095***	–0.007
	(0.042)	(0.006)	(0.022)	(0.005)
RIF earnings structure	–0.347***	–0.059***	–0.072***	–0.090***
	(0.046)	(0.011)	(0.022)	(0.014)
RIF reweighting error	–0.002	–0.001***	–0.004	0.000***
	(0.005)	(0.000)	(0.004)	(0.000)
RIF detailed decomposition				
RIF composition				
RTI	–0.006*	–0.001	–0.002	–0.001
	(0.003)	(0.001)	(0.001)	(0.001)
Age	0.019***	0.004***	–0.010***	–0.006***
	(0.004)	(0.001)	(0.002)	(0.001)
Sex	–0.000	–0.001	–0.000	–0.000*
	(0.001)	(0.000)	(0.000)	(0.000)
Education	–0.012***	–0.006***	–0.008***	0.000
	(0.003)	(0.001)	(0.002)	(0.000)
Total composition	0.001	–0.004	–0.02	–0.007
RIF earnings structure				
RTI	–0.025	0.042***	–0.016	–0.107***
	(0.036)	(0.008)	(0.025)	(0.010)
Age	–0.150	–0.045*	–0.181**	0.208***
	(0.113)	(0.023)	(0.080)	(0.023)
Sex	0.072	–0.268***	0.186**	0.136***
	(0.120)	(0.018)	(0.076)	(0.017)
Education	–0.087	0.263***	0.073	0.118***
	(0.155)	(0.026)	(0.075)	(0.024)
Intercept	–0.157	–0.051	–0.135	–0.445***
	(0.209)	(0.045)	(0.149)	(0.042)
Total earnings structure	–0.347	–0.059	–0.073	–0.09

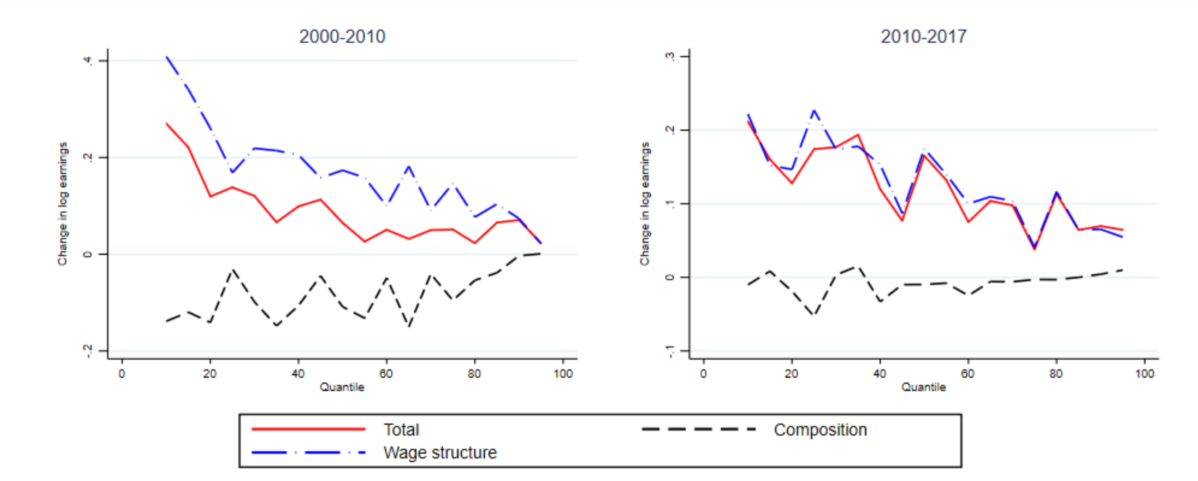
Note: robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: authors' illustration based on ENPE data.

Figure A17: Baseline composition: RIF decomposition of total earnings change into wage structure and composition effects
(a) Country-specific RTI



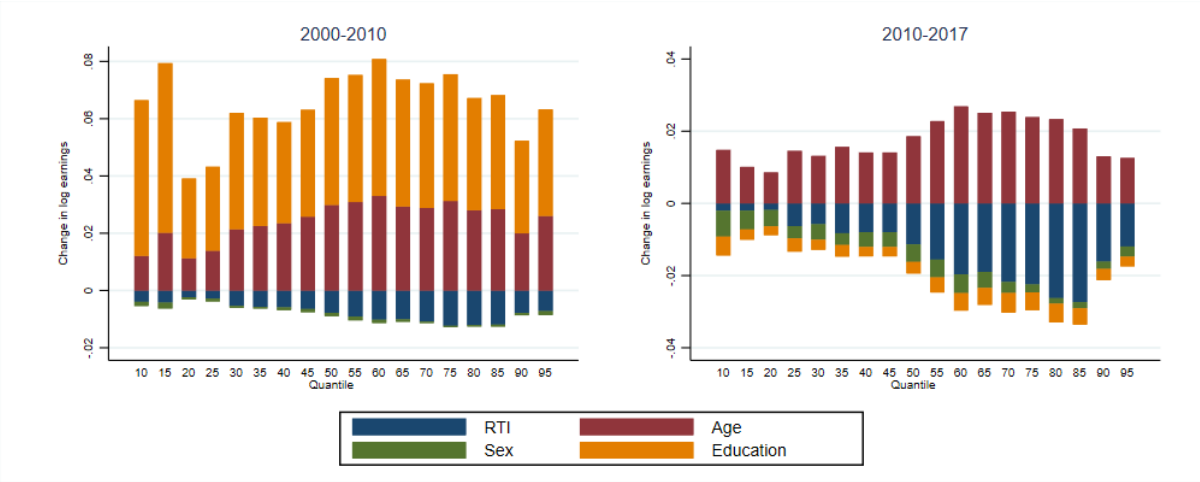
(b) O*NET RTI



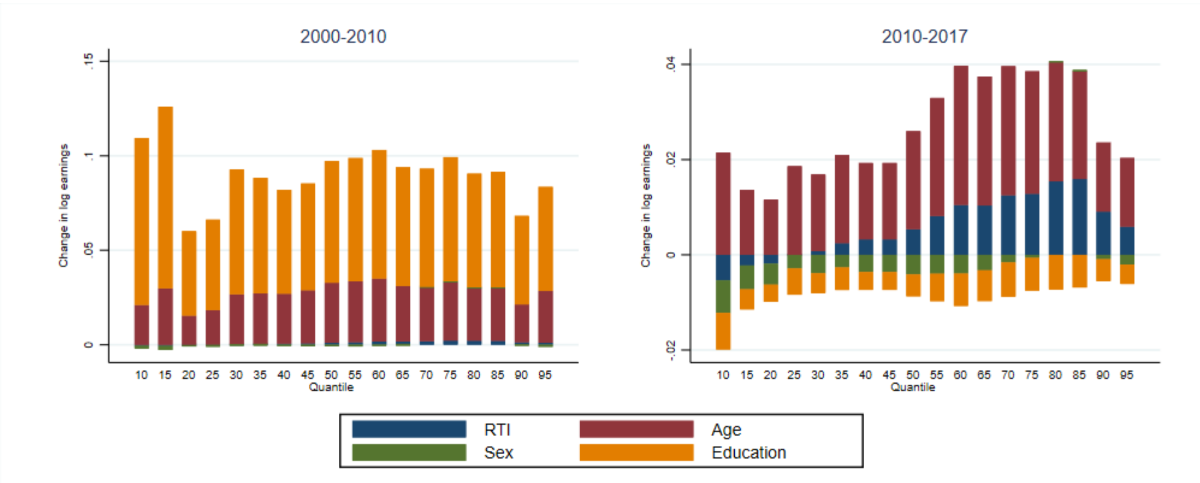
Source: authors' illustration based on ENPE data.

Figure A18: Baseline composition: detailed RIF decomposition of determinants of earnings changes: composition effects

(a) Country-specific RTI

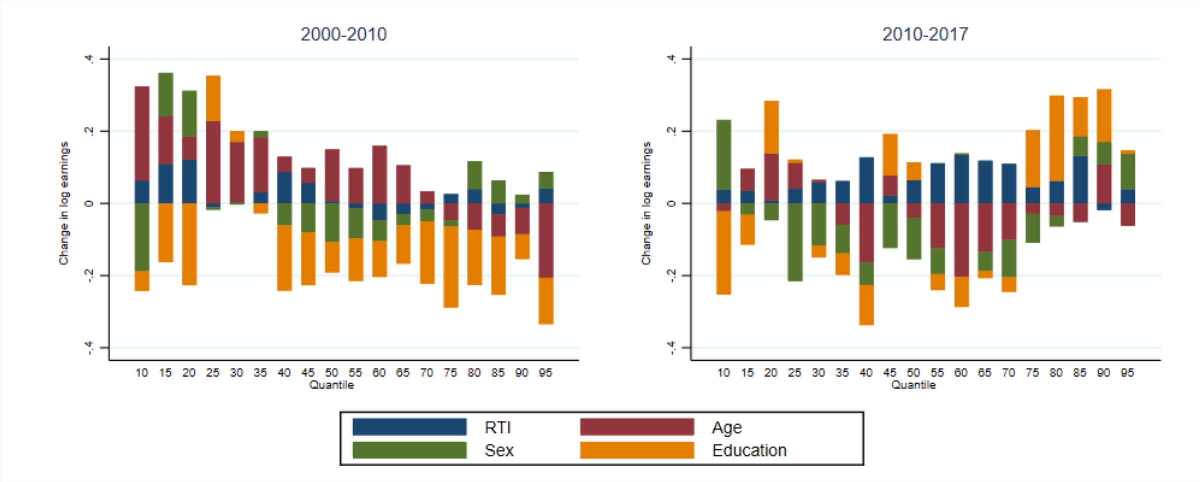


(b) O*NET RTI

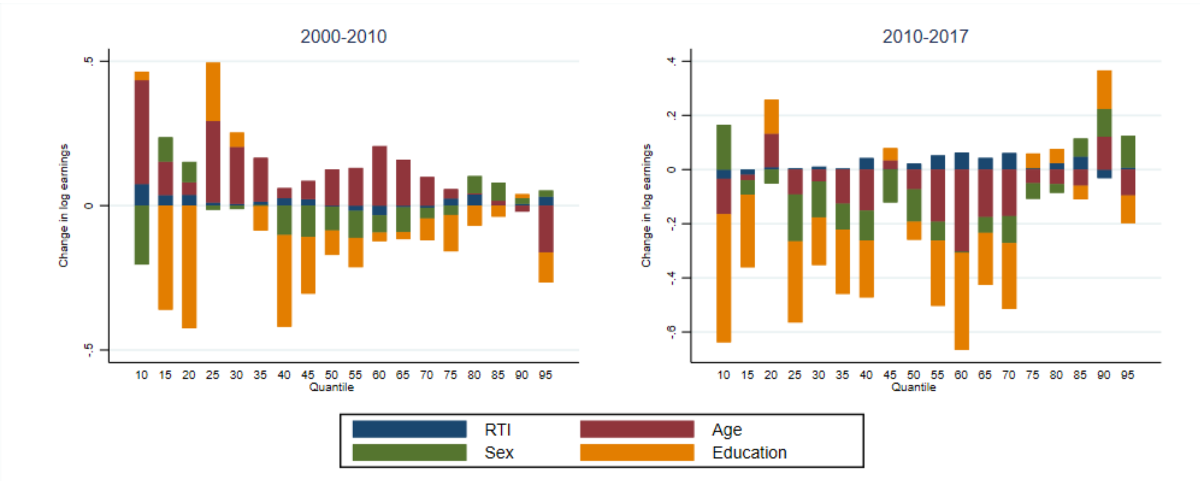


Source: authors' illustration based on ENPE data.

Figure A19: Detailed RIF decomposition of determinants of earnings changes: wage structure effects
(a) Country-specific RTI



(b) O*NET RTI



Source: authors' illustration based on ENPE data.