Marouani, Mohamed Ali; Le, Phuong Minh

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Inequality and occupational change in times of Revolution:

The Tunisian perspective

Mohamed Ali Marouani[1*] and Phuong Minh Le[2*†]

[(*)] UMR Développement et Sociétés, Université Paris 1 Panthéon-Sorbonne and Institut de Recherche pour le Développement

[(†)] The Centre for Analysis and Forecast, Vietnam Academy of Social Sciences

Abstract

The public sector plays a large role in many developing economies, but its effect on earnings inequality dynamics has not been widely studied. In this paper, we investigate the earnings inequality trends and their determinants in the decades before and after the Tunisian Revolution, focusing on the impact of public wage and employment policy changes. A recentered-influence function (RIF) decomposition is performed to decompose the change in earnings into wage structure and composition effects and to assess the contribution of various determinants of inequality change. We find that earnings inequality decreased significantly during the period of investigation in Tunisia, mainly due to the decrease in the public–private wage gap and in sector wage gaps on the demand side, and the decreasing education premia on the supply side. The increase in marginal returns to average routine-task intensity jobs, the falling return to experience, and the decreasing regional wage gap also contributed to declining earnings inequality, but to a lesser extent.

Keywords: wage inequality, Revolution, occupational change, education premium, public wage policy

JEL codes : J21, J23, J24, J32, J45

[1] Email addresses: Mohamed-Ali.Marouani@univ-paris1.fr, minh-phuong.le@etu.univ-paris1.fr.

[2] Corresponding author. Tel.: +33 82 91 89 36

1 Introduction

The relationship between political change and inequality is not easy to apprehend, as causality can go both ways (Thorbecke and Charumilind, 2002). As shown by Alesina and Perotti (1996), inequality is a source of social tensions that lead to political instability. This cross-country analysis has, however, been recently challenged by the Arab Spring. Devarajan and Ianchovichina (2018) show that inequality did not fuel the uprisings, as it was decreasing in countries where it started. People were dissatisfied because the government was no longer able to provide jobs and high-quality public services. This is in line with Thorbecke and Charumilind (2002), who consider that what really matters is the gap between expectations and achievements. The importance of perceptions is confirmed by Gimpelson and Treisman (2018), who show that there is a strong correlation between conflict and perceived inequality, while there are none with actual income distribution outcomes.

Conversely, we find a large literature on the impact of political regimes on inequality (among others, Alesina and Rodrik (1994); Bourguignon and Verdier (2000)), but the effects of political change on distribution seems to have been studied less, at least from an economic point of view. Our objective in this paper is to empirically investigate the evolution of inequality during political transition from dictatorship to democracy. Our aim is to identify regularities explained by structural factors, such as education or computerization, and highlight changes that may have occurred due to increasing social pressures, resulting from regime change.

As a case study, we use Tunisia before and after the 2011 revolution. 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%. In the last 20 years, youth unemployment has been severe, particularly for graduates.[3] Coupled with a widely shared sentiment of political discontent and rising cronyism among the population (Rijkers et al., 2017), the labor market outcomes fueled the Revolution of 2011 with a long-lasting impact for the whole Middle East and North Africa (MENA) region. MENA is, however, not an exception. In many places in the world, the combination of a youth bulge and low demand for skills have induced unemployment, overeducation, frustration, and rebellion (Urdal, 2006; Nordås and Davenport, 2013).

We adopt a labor market lens to analyze inequality and, thus, focus on the evolution of earnings distribution. We test the contribution of different factors highlighted in the literature on developed and developing countries and add the role of the public sector, given its importance in the MENA social contract, as well as in other regions of the world. Given that public wages are generally less dispersed than private ones, the size of the public sector can affect wage inequality (Wallerstein, 1999).

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. The canonical model formalizes the two forces of "Tinbergen's race" between technology and skills supply by considering high- and low-skill workers as imperfect substitutes. With the dramatic increase of education in the 20th century, if technology remained constant, education premia would have fallen significantly (Acemoglu and Autor, 2011). While education premia have generally increased in developed countries and particularly in the U.S. (Autor, 2014), Ferreira et al. (2021) show that lower education premia are among the significant driving forces of falling earnings inequality in Brazil between 1995 and 2012. However, they also show that a reduction of returns to the labor market experience played a much bigger role in reducing pay inequality.

[3] Between 30% and 40%, according to Asik et al. (2020).

Influential and growing literature (Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013) 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 U.S. 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 by high intensity of manual and cognitive tasks, respectively. While this work was ground-breaking, it remains biased toward 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 and find little evidence. 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 labor productivity in manufacturing, which pushes labor in the 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 toward 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 before and after the Revolution. The second objective is to identify the main factors underlying these employment and earnings dynamics and elucidate their mechanism. A recentered 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. Highlighting the role of the Revolution mainly through its impact on public wage and employment 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, mainly due to decreases in the public–private wage gap and sector wage gap on the demand side and the decreasing education premia on the supply side. The increase in marginal returns to low-wage but average-RTI jobs, the falling return to experience, and the decreasing regional wage gap are also found to have contributed to the decline in overall earnings inequality.

2 Data

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 the labor market and household conditions from 2000, 2010, and 2017. In addition to labor 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 labor 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 provides the occupational code (Nomenclature Nationale des Professions, NNP), 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.

In order to estimate the contribution of the Routine-biased technical change to the earnings inequality changes, we use the task-content measure 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 tasks: 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 technical changes and employment in developed countries (see Goos and Manning, 2007; Autor et al., 2008; Acemoglu and Autor, 2011; Jaimovich and Siu, 2012; Foote and Ryan, 2015; Graetz and Michaels, 2017).

Merging the two data sets requires us to map the two occupational code systems O*NET- SOC and NNP into the four-digit ISCO-88 occupations.[4] Among the three waves of the survey to which we have access, two waves (2000 and 2010) use NNP-97 (1997 NNP), corresponding to ISCO-88; the third wave, in 2017, uses NNP-14 (2014 NNP), 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 ISCO88 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). 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. As 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 A decrease in inequality over the two decades

[4] ISCO, International Standard Classification of Occupations.

3.1 Overall inequality indicators

Labor 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 sub-period witnessed a rapid fall in earnings inequality, with the Gini index dropping by 4 percentage points over 10 years. This reduction halved to around 2 percentage points in the second sub-period. The Lorenz curves in Figure 3.1 provide an illustration of these trends.

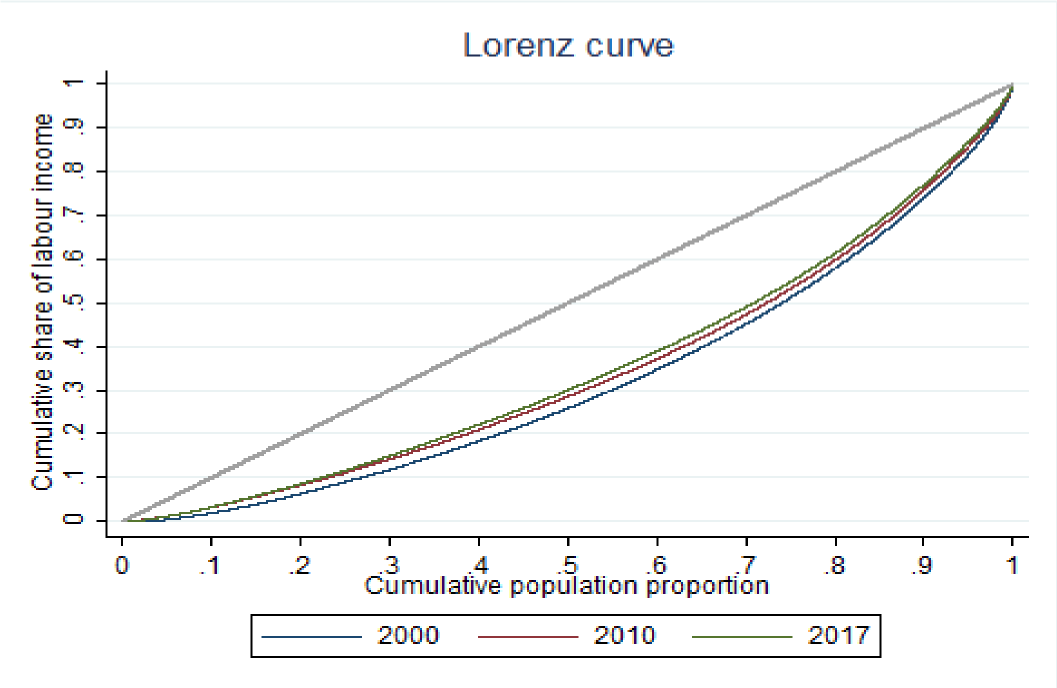

Figure 3.1: Lorenz curves showing trends in labor income inequality

While the reduction is clear at the aggregate level, the evidence also suggests 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 percentile decreased more than those in the top 90th to 50th percentile (Table 3.1). The earnings gap between the 90th and the 50th percentile narrowed mostly during the post-Revolution period, whereas the earnings gap between the 90th and 10th percentile contracted more in the pre-Revolution period. As we will argue in later sections, this decrease of inequality mainly came from the relative improvement of wages for low-wage workers and, to a lower extent, medium-wage workers.

Table 3.1: Summary inequality indices and interquantile ratios

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

Examining the earnings growth by percentile (Figure 3.2), we see a high growth in low wages from 2000 to 2010 (particularly for the lowest decile) but a lower increase of earnings in low-wage jobs in the 2010–2017 period. We also see opposite patterns for medium-income earners, whose earnings growth was relatively flat in the pre-Revolution period, and increased, particularly for the second to the sixth decile. Higher wages also improved but to a significantly lesser extent.

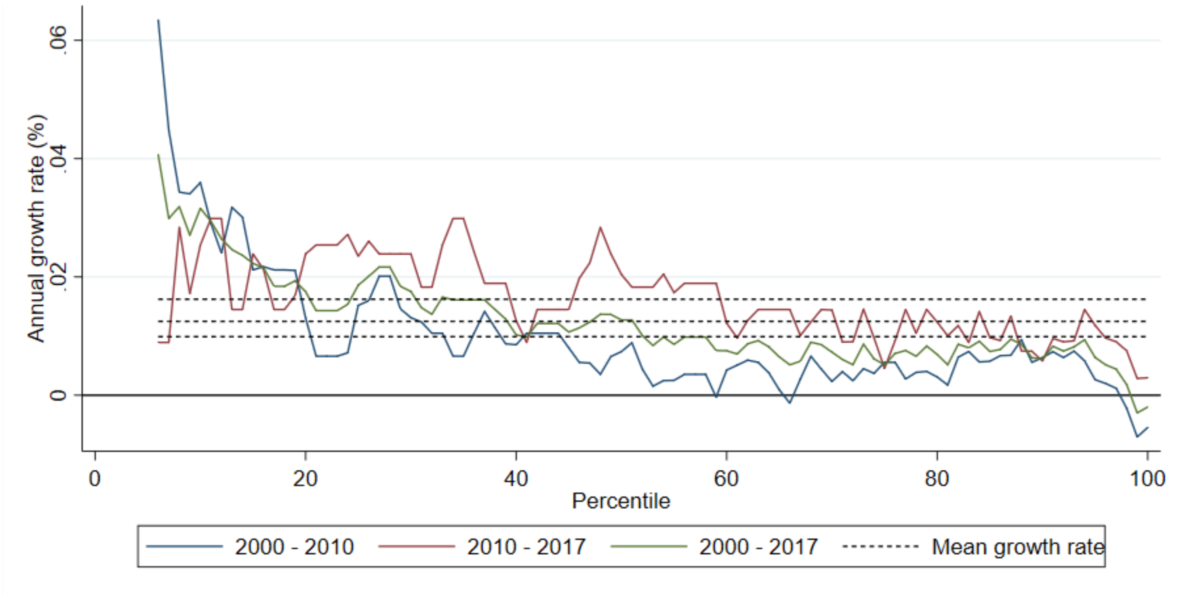

Figure 3.2: Growth incidence curves of the wage distribution

3.2 An occupational perspective

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 (Figure 3.3), we find some stable results over the whole period of investigation and some that vary with the sub-period.[5] 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, medium-skill jobs increased in the second sub-period.

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

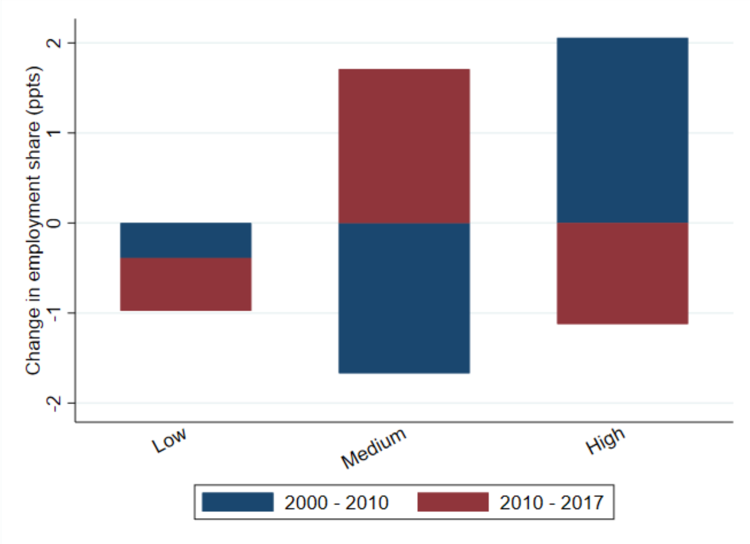

Figure 3.3: Change in employment share by skill level

Table 3.2: Change in employment and earnings by occupational group

Panel A: Employment share (%)

	Level			Percentage change	
	2000	2010	2017	2000-10	2010-17
1 Managers	3.53	3.39	3.20	-0.14	-0.19
2 Professionals	10.74	11.22	10.94	0.48	-0.28
3 Technicians	6.68	6.90	5.36	0.22	-1.54
4 Clerks	9.79	7.51	5.38	-2.28	-2.13
5 Services	10.12	10.91	14.35	0.80	3.44
6 Skilled Agricultural	3.88	3.11	4.74	-0.76	1.63
7 Trades Workers	14.85	13.79	13.92	-1.05	0.13
8 Machine Operators	15.28	15.97	14.93	0.69	-1.04
9 Elementary	25.15	27.19	27.16	2.04	-0.03

Panel B: Mean weekly earnings (constant 2010 prices)

	Level			Annual growth rate *	
	2000	2010	2017	2000-10	2010-17
1 Managers	193.53	202.43	164.60	0.45	-2.91
2 Professionals	161.61	173.44	179.65	0.71	0.50
3 Technicians	121.80	122.64	138.53	0.07	1.76
4 Clerks	102.09	101.58	109.58	-0.05	1.09
5 Services	83.97	80.34	91.76	-0.44	1.92

6 Skilled Agricultural	44.71	50.96	61.25	1.32	2.66
7 Trades Workers	69.68	81.18	91.52	1.54	1.73
8 Machine Operators	69.62	74.16	82.63	0.63	1.56
9 Elementary	51.54	59.13	75.32	1.38	3.52

(*) Compound annual growth rate.

Digging deeper at the one-digit occupational level (Table 3.2), 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, as 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 sub-period were characterized by a significant decrease after 2010. This is due to shrinking activity in the transport and telecom sectors after the Revolution. On the other 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 (Appendix Table A.3.1). This increase after the Revolution was due to the significant increase in the hiring of security forces (policemen, national guard, etc.). Shop salespersons also increased significantly, as well as housekeepers and restaurant service workers.

4 Underlying factors of the inequality trend

4.1 The high pace of education expansion and the fall of education premium

Tunisia experienced a high pace of education expansion over the pre-revolution period. The gross tertiary enrollment ratio of Tunisia increased on average 1.4 percentage point per year from 2000 to 2011, whereas the average of the world and the MENA region was about 1.1 percentage point[6]. 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). Figure 4.4 plots the cumulative number of college graduates and employed college graduates from 2000 to 2017. The number of college graduates having a job always floated around 50% of the total number of Tunisian college graduates.[7]

[6] Authors' calculations from the World Bank's data. Gross enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education shown. Source: https://data.worldbank.org/indicator.

[7] This includes both active and inactive working population. If only active working population is taken into account, the unemployment rate of Tunisian graduates was about 10.4% in 2001 and soared to 22.9% in 2010 (**?**, 45–75) and 30% in 2017 (Kthiri, 2019).

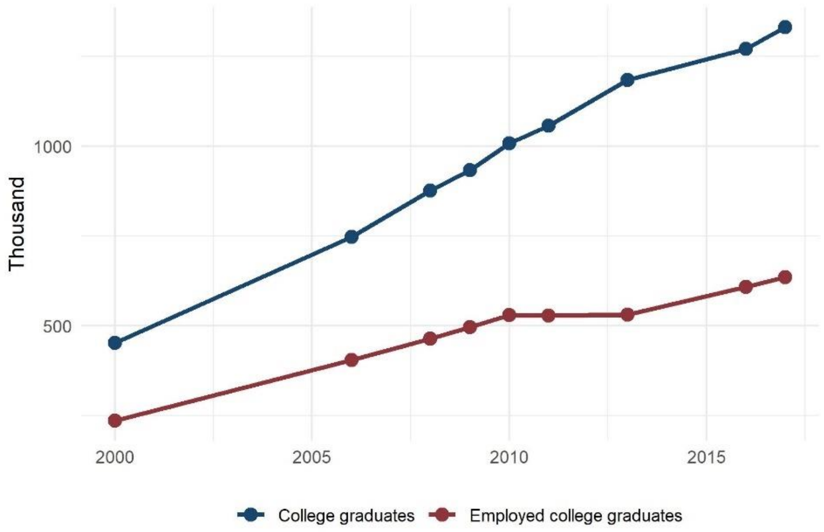

Figure 4.1: The supply and demand of college graduates, 2000–2017

This relative increase of skill supply drove down the market return to skill, or education premium. As shown in Figure 4.1, the earnings premium for tertiary education decreased for both men and women. In 2000, men and women educated at tertiary levels gained 27 and 24 percentage points, respectively, of a premium above those who had a secondary level of education. These differences had reduced to 17 and 20 percentage points, respectively, by 2017.

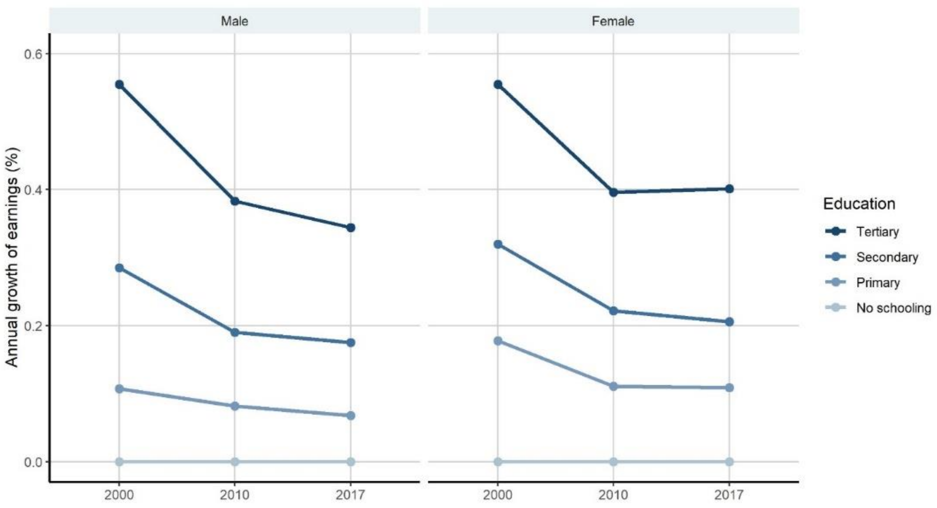

Figure 4.2: Change in the education premium on log earnings by gender

Although the education premium has been decreasing sharply since 2000 (Figure 4.2), 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.

Changes in the observed education premium may not only reflect changes in the price of skills but also changes in the composition of jobs across schooling groups. In other words, as the supply of skills increases, if demand does not follow, some college graduates are obliged to accept jobs that require a lower skill level than their skill level. This phenomenon is often referred as “over-education” (Kupets, 2016; Leuven and Ooster-beek, 2011). If it is true, we should observe a shift of the highly educated group toward lower-skilled jobs. Our plot (Figure 4.3) of the share of low-, medium-, and high-skilled jobs within each schooling group confirms the over-education phenomenon in the Tunisian labor market. It shows that the relative medium- and low-skilled jobs performed by the tertiary educated group increased at the expense of high-skilled jobs.

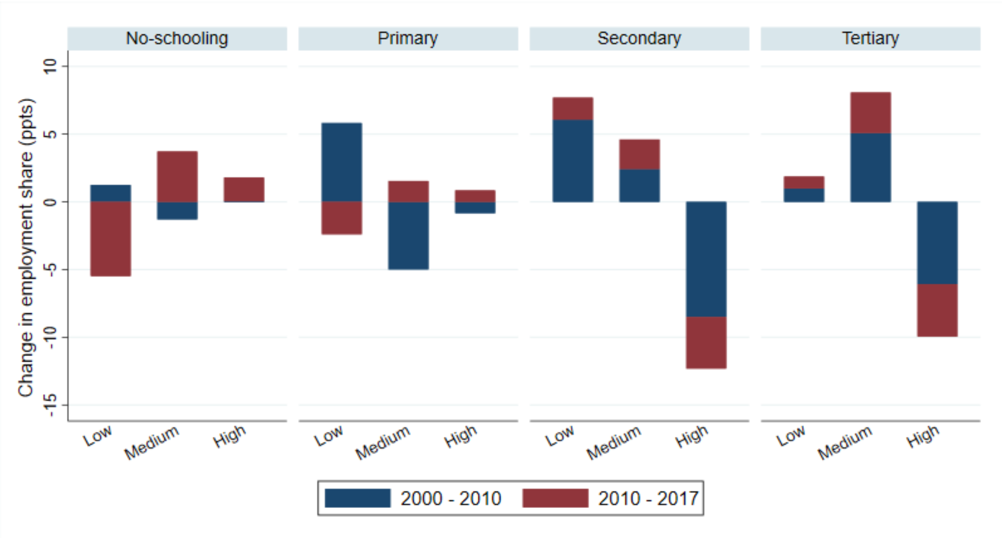

Figure 4.3: Change in employment share by education and skill level

4.2 The unclear role of technical change

Although the expansion of education may be a crucial factor, it does not alone determine the changes in education premium and ultimately earnings inequality. The education premium results from the interplay between the supply and demand of skills. As a result, it does not decline as long as the skill demand increases at an equivalent or higher pace than the skill supply. This is the case of many developed countries where the education premium kept increasing with the education upgrading of the labor force, thanks to the dominating effect of the technology-driven demand of skills (see Levy and Murnane (1992), Acemoglu (2002), Autor and Dorn (2013) for the U.S.; Goos and Manning (2007) for the U.K., and Goos et al. (2014) for Europe). According to Autor et al. (2008), the skill-biased technical change hypothesis is a good starting point to explain rising education premia in the U.S., but it has to be complemented with a task-based analysis to take into account the impact of the information technology revolution. Technical change, on one hand, replaces the repetitive tasks performed by low- and middle-skilled workers, and on the other hand, creates new tasks that require an input combination of technologies and high-skilled workers performing abstract tasks. This mechanism, the “Routine-biased technical change” (RBTC), was formalized by Acemoglu and Autor (2011) and has been widely accepted as the main economic culprit of the famous vanishing of the middle class in the U.S. The role of technical change in developing countries’ labor market is, however, still far from clear. Though our above preliminary description of the data suggests that RBTC may play some role in shaping the recent inequality trends, more diagnoses need to be carried out to detect the presence of the RBTC in Tunisia’s labor market.

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:

$$\Delta \text{ EmploymentShare }_{i,t} = \beta_0 + \beta_1 \text{ Earning } s_{i,t-1} + \beta_2 \text{ Earnings }^2_{i,t-1} \tag{4.1}$$

If there exists a polarization pattern, the coefficient of the linear term should be found significantly negative, while the coefficient of the quadratic term is 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 the employment share. Hence, Sebastian (2018) extended this specification to the relationship between wage growth and the initial wage level:

$$\Delta\log \text{ Earnings }_{i,t} = \beta_0 + \beta_1 \text{ Earnings}_{i,t-1} + \beta_2 \text{ Earnings }^2_{i,t-1} \tag{4.2}$$

Table 4.1: Job and earnings polarization tests presents our quadratic regressions of changes in employment share and mean log earnings on the initial level of mean log earnings. The regressions using the median log earnings, as in Goos and Manning (2007), are presented in Appendix Table A.4.1. Although no significant evidence of employment polarization is found in Tunisia, the regression of log earnings growth on the initial mean log earnings provides support for the earnings polarization in the first sub-period. Despite the significant regression estimates, the plot of the changes in mean log earnings over skill percentiles (Figure 4.4) shows 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 4.1: Job and earnings polarization tests

Dependent variable: Change in employment share

	2000-2010	2010-2017	2000-2017
Initial mean log earnings	-2.233	-1.391	-5.579
	-11.781	-8.635	-10.807
Sq. Initial mean log earnings	0.199	0.149	0.565
	-1.252	-0.91	-1.159
Constant	5.955	3.049	13.381
	-27.561	-20.235	-24.911
Observations	103	102	101
R-squared	0.029	0.001	0.046
F-test	0.788	0.985	0.679

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

Dependent variable: Change in mean log earnings

	2000-2010	2010-2017	2000-2017
Initial mean log earnings	-1.659***	-1.062*	-1.936***
	-0.499	-0.623	-0.691
Sq. Initial mean log earnings	0.173***	0.096	0.184**
	-0.056	-0.067	-0.076
Constant	4.009***	2.940**	5.121***
	-1.088	-1.447	-1.558
Observations	103	102	101
R-squared	0.284	0.385	0.53
F-test	0	0	0

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

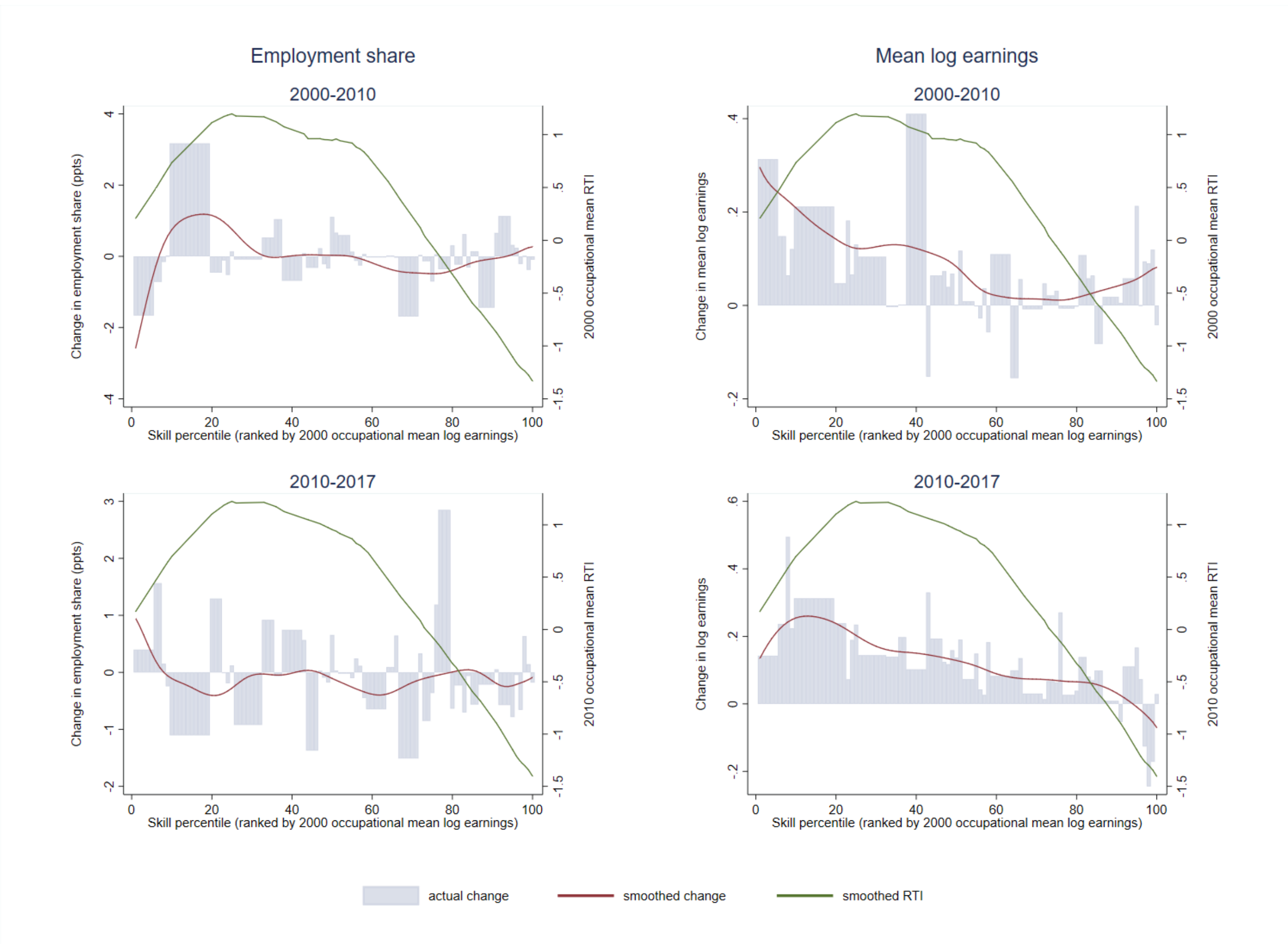

Figure 4.4: Change in mean log earnings and employment share by skill percentiles

One might think that the polarization was 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 Appendix Table A.4.3, our results remain stable even after the removal of this sector.

We also consider the effect of the public sector since its role as jobs provider has increased sharply in the aftermath of the Revolution. 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% from 2010 to 2017, while the share of the public administration fluctuated around 20% of the employee population in Tunisia.[8] After excluding the public sector from the analysis, we still do not find any sign of job polarization, but we even find a reverse U-shaped pattern in the first sub-period (Appendix Table A.4.4).

Although the above polarization tests are intuitive and simple to be implemented, they are less effective when there exists other patterns of occupational evolution, for example, as shown in Section 3, 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. Therefore, we further investigate the routinization hypothesis using a direct measure of the routine task intensity, the O*NET RTI, constructed by Acemoglu and Autor (2011). The index ranges from -4.35 to 2.92, where higher value corresponds to higher intensity of routine tasks. Before looking for any relationship between RTI and the evolution of jobs and earnings, we need to answer an elemental question: where are the high-RTI jobs located in the earnings distribution? In other words, are the high-RTI jobs low-, medium-, or high-paid jobs? To answer this question, we plot the average three-digit-occupation RTI against the rank of 2000 occupational mean log earnings in Figure 4.4. As we can see, the highest-RTI jobs are the middle jobs while the lowest-RTI jobs are situated at the upper end of the earnings distribution. This is consistent with the observations of Autor and Dorn (2009), Acemoglu and Autor (2011), Goos and Manning (2007), and many other authors using the O*NET RTI.

The narrative departs from the previous works when it comes to the evolution of RTI overtime. Indeed, we found a contrasting trend with the trend of RTI in advanced countries. During the 2000–2010 period, the average RTI increased from 0.529 to 0.602, then slightly decreased over the second sub-period, but until 2017 it had not come back to the 2000 level. This does not, however, contradict our finding of an L-shape earnings polarization before the Revolution because the winners in terms of earnings and employment share during this period are the low-paid but average-RTI jobs. As a result, we have a coexistence of an L-shape earnings polarization and an increase of the overall RTI. Although the same trends continued after the Revolution, they were much flatter. The share of high-RTI jobs continued to decrease, but so did the share of low- (negative-) RTI jobs. The winners in terms of earnings were still the same, but their earnings improved less. In conclusion, technical changes may play a certain role in shaping the demand in Tunisia's labor market, but this role seems to be very small in comparison to other factors.

4.3 A sluggish structural transformation

[8] Authors' calculations based on INS data.

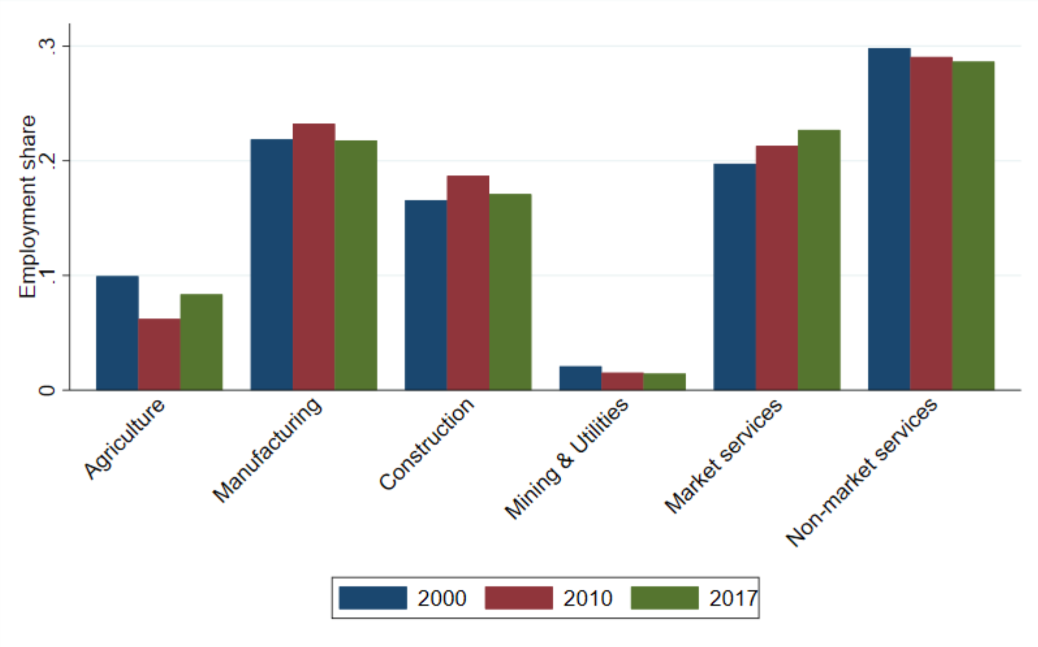

Figure 4.5: Employment distribution by sector 2000–2017

As shown in Figure 4.5, the sectoral distribution of employment helps understand some of the previous dynamics. The share of agriculture in employment increased for the first time in 2017 after a decline in 2010, which started a few decades ago (Marouani and Mouelhi, 2016). Moreover, the share of manufacturing in 2017 is back to its level of 2000 after an increase in the first decade of the new millennium. This movement of deindustrialization is in favor of services of which share continuously increased between 2000 and 2017. Construction also witnessed a similar movement than manufacturing due to an anemic growth decade.

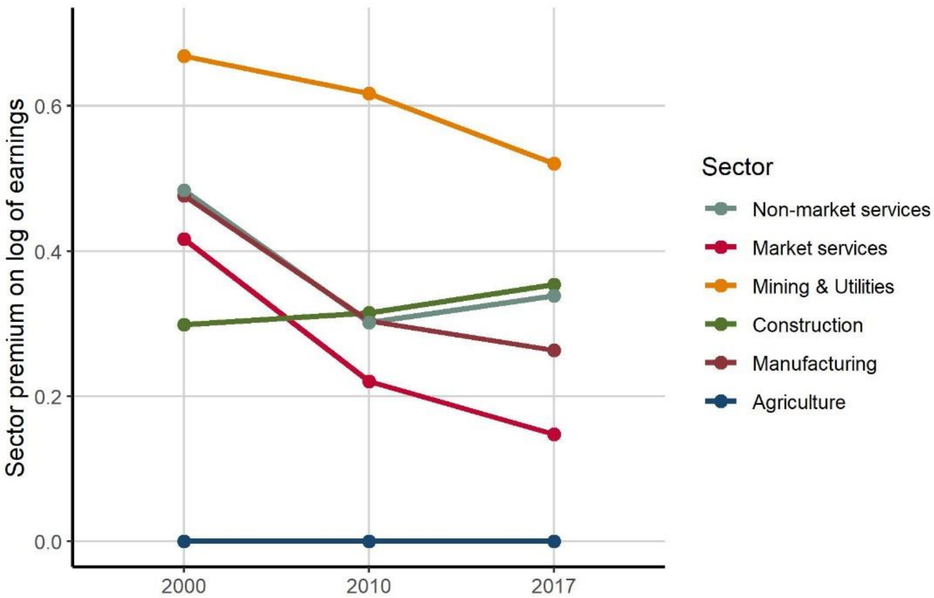

Figure 4.6: Change in the sector premium on log earnings

Looking at earnings gives very interesting insights. Figure 4.6 depicts the changes in sector premium over the two decades, using agriculture as the base sector. Except for construction and non-market service industry, we observed a wage convergence elsewhere across sectors during the examined period. From a structural-change point of view, this is due to the outflow of workers from agriculture, which reduced the labor supply and consequently the wage gap between agriculture and other sectors. The same explanation can be applied to the case of manufacturing. Because of the service-led deindustrialization, the process of wage gap closing with agriculture was slower in manufacturing than in services. Comparing the two sub-periods, we see that the sector premium reduced more strongly before the Revolution, which is congruent with the sharp decline of inequality during this sub-period.

4.4 Public wage and employment policies as a redistribution tool

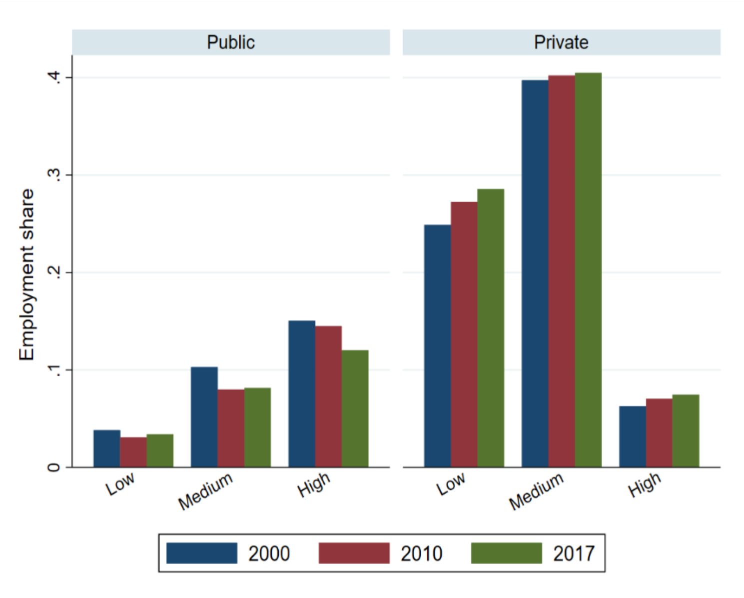

Figure 4.7: Employment shares in public and private sector by skill levels

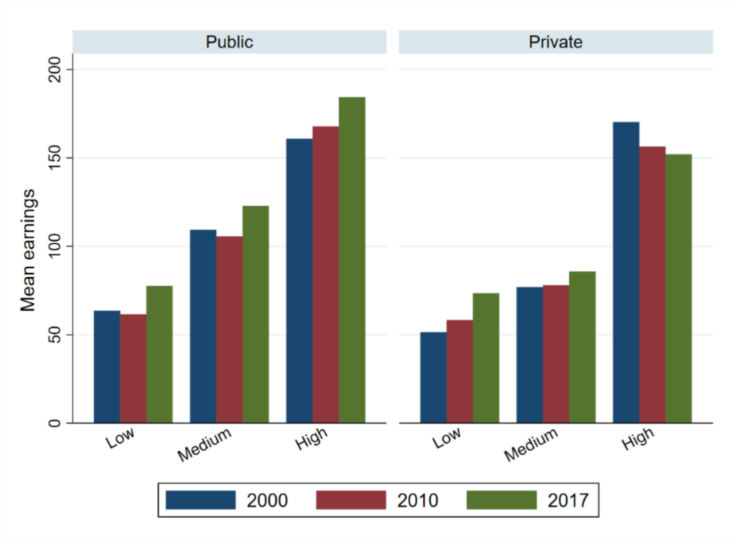

Figure 4.8: Earnings in public and private sector by skill levels

Figure 4.7 and Figure 4.8 compare the evolution of employment shares and earnings of workers by skill level between 2000 and 2017. The first observation is that the share of low-skilled workers increased in the private sector, while it kept its 2000 level in 2017 in the public sector. The share of medium-skilled workers increased slightly in the private sector and decreased significantly in the public sector before the Revolution but did not vary after the Revolution. High-skilled workers in the private sector have a similar trend to that of medium-skilled workers in the private sector, but their share is reduced in the public sector, particularly after the Revolution. This can be explained by the new requirements of the period, mainly in terms of security, but also to the nature of the pressure, which was maybe more exerted by the lowest deciles of the population.

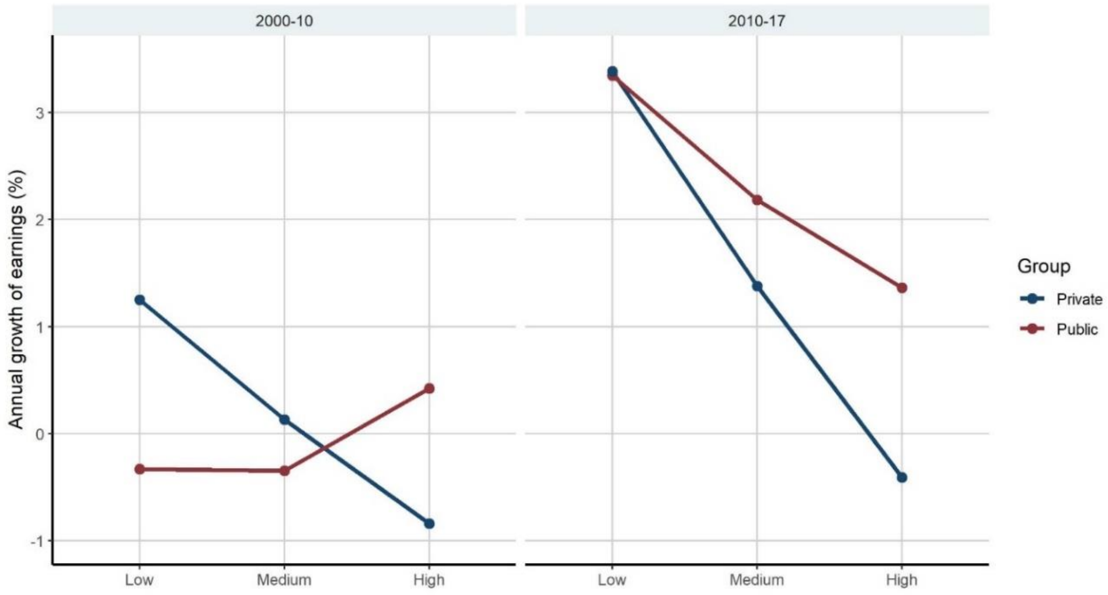

Figure 4.9: Change in earnings by skill level in the public and private sector

The earnings dynamics shown in Figure 4.9 reveal a substantial change in public wage policy in the decade following the Revolution. Indeed, before the 2010 uprisings, the earnings evolution of public sector was characterized by a disequalizing change across occupations. Public high-skilled workers benefited an average annual earnings growth of 0.4%, while the other skill groups had their earnings reduced on average by 0.3% per year. On the contrary, the between-skill-groups earnings difference decreased significantly in the private sector. Private high-skilled workers saw their earnings falling considerably, from above to below the earnings level of their public counterparts (Figure 4.8). This highlights an additional source of the decline in earnings inequality observed in this sub-period. The 2011 Revolution reversed the public wage policy. Thenceforth, the public sector joined the private sector in the wage-equalizing tendency. Although the earnings growth rate of public qualified workers still increased, it was far below the earnings growth rate of public low-skilled workers. This change came as no surprise, given the urgency to attenuate social tensions. As public and private earnings followed the same trends across skill groups, we expect that the change in public-private earnings gap would be smaller and have a lower effect on the overall change of earnings inequality.

5 Decomposition of inequality decline

5.1 Methodology

How much do these factors contribute to the decline of earnings inequality over the last decades? To answer this question, we use Firpo et al.'s (2018) reweighted recentered influence function decomposition, an extended version of Oaxaca-Blinder decomposition to other distributional statistics besides the mean, including the Gini index, quantiles, interquantile ranges, etc. The method is detailed as follows: The decomposition framework and the reweighting method are presented in

Section 5.1.1. Section 5.1.2 introduces the recentered-influence function, and finally, Section 5.1.3 presents our model.

5.1.1 “Reweighted-regression” decomposition

Oaxaca-Blinder (OB) decomposition has been widely used in labor economics to estimate the wage discrimination against one group by the other. More precisely, it breaks down the mean wage difference between two groups into the difference in groups’ characteristics distributions (composition effect or explained part) and the difference in the labor market returns to groups’ characteristics (wage structure effect or unexplained part), resulting from the market discrimination.

Let Y_t and X_t be the (natural) log wages and the vector of the predictors; let β_t be the vector of the coefficients resulting from a linear regression of Y_t on X_t; let t ∈ {0,1} be the indicator for group membership. The difference in the mean of the log wages can be divided as follows:

$$\bar{Y}_1 - \bar{Y}_0 = \underbrace{(\bar{X}_1 - \bar{X}_0)'\hat{\beta}_0}_{\text{explained}} + \underbrace{\bar{X}_1{}'(\hat{\beta}_1 - \hat{\beta}_0)}_{\text{unexplained}} \tag{5.1}$$

Interpreting the explained part is straightforward: it measures the expected change in Group 0’s mean wage if it had Group 1’s mean characteristics. The unexplained part, however, needs a further division to be interpreted:

$$\bar{X}_1{}'(\hat{\beta}_1 - \hat{\beta}_0) = \bar{X}_0{}'(\hat{\beta}_1 - \hat{\beta}_0) + (\bar{X}_1 - \bar{X}_0)'(\hat{\beta}_1 - \hat{\beta}_0) \tag{5.2}$$

The first term in equation (5.2) measures the expected change in Group 0’s mean wage if it had Group 1’s market returns to characteristics, whereas the interaction term measures the expected change in Group 0’s mean wage when it had both Group 1’s characteristics distribution and market returns at the same time.

Equation (5.1) provides a measurement of the wage discrimination against Group 0, with 1 as the base group. An equivalent equation can be formulated to estimate the wage discrimination against Group 1, with 0 as the base group:

$$\bar{Y}_1 - \bar{Y}_0 = (\bar{X}_1 - \bar{X}_0)'\hat{\beta}_1 + \bar{X}_0{}'(\hat{\beta}_1 - \hat{\beta}_0) \tag{5.3}$$

However, neither $\hat{\beta}_0$ nor $\hat{\beta}_1$ is satisfying as a counterfactual wage structure (or base group), because they may not reflect the appropriate wage structure of the other group in the absence of the market discrimination (Firpo et al., 2011). Many alternatives have been proposed. For example, Neumark (1988) suggested using the coefficients from a pooled linear regression. The mean wage difference, then, is expressed as follows:

$$\bar{Y}_1 - \bar{Y}_0 = (\bar{X}_1 - \bar{X}_0)'\hat{\beta}^* + \left[\bar{X}_1{}'(\hat{\beta}_1 - \hat{\beta}^*) + \bar{X}_0{}'(\hat{\beta}^* - \hat{\beta}_0)\right] \tag{5.4}$$

Jann (2008) suggested including a group indicator variable in the pooled model in case some of the unexplained parts of the differential are inappropriately transferred into the explained component. Another concern was raised by Barsky et al. (2002) about the linear assumption of the OB decomposition. Indeed, it may yield inconsistent estimates of both composition and wage structure effects if the conditional mean function is non-linear. Therefore, we use the non-parametric reweighting procedure introduced by DiNardo et al. (1996) to construct the counterfactual. The idea is to replace the marginal distribution of X_1 with the marginal distribution of X_0 using the following reweighting factor:

$$\Psi(X) = \frac{\Pr(X \mid T_1 = 0)}{\Pr(X \mid T_1 = 1)} = \frac{\Pr(T_1 = 0 \mid X)/\Pr(T_1 = 0)}{\Pr(T_1 = 1 \mid X)/\Pr(T_1 = 1)} \tag{5.5}$$

where T_t ($t \in \{0,1\}$) is a dummy variable indicating the group membership of an individual. The "reweighted-regression" decomposition, as called by Firpo et al. (2011), then has the following form:

$$\bar{Y}_1 - \bar{Y}_0 = \underbrace{\left(\bar{X}_1{}'\hat{\beta}_1 - \bar{X}_0^C{}'\hat{\beta}_0^C\right)}_{\text{unexplained}} + \underbrace{\left(\bar{X}_0^C{}'\hat{\beta}_0^C - \bar{X}_0{}'\hat{\beta}_0\right)}_{\text{explained}} \tag{5.6}$$

where superscript C denotes the counterfactual. The composition effect (explained) can be divided into a pure composition (pure explained part) component and a specification error component, which would be close to zero if the model is linear:

$$\bar{X}_0^C{}'\hat{\beta}_0^C - \bar{X}_0{}'\hat{\beta}_0 = \underbrace{(\bar{X}_0^C - \bar{X}_0)'\hat{\beta}_0}_{\text{pure explained}} + \underbrace{\bar{X}_0^C{}'\left(\hat{\beta}_0^C - \hat{\beta}_0\right)}_{\text{specification error}} \tag{5.7}$$

The wage structure effect (unexplained) can be divided into a pure wage structure (pure unexplained part) component and a reweighting error component, which would be close to zero if the estimate of $\Psi(X)$ is consistent:

$$\bar{X}_1{}'\hat{\beta}_1 - \bar{X}_0^C{}'\hat{\beta}_0^C = \underbrace{\bar{X}_1{}'\left(\hat{\beta}_1 - \hat{\beta}_0^C\right)}_{\text{pure unexplained}} + \underbrace{(\bar{X}_1 - \bar{X}_0^C)'\hat{\beta}_0^C}_{\text{reweighting error}} \tag{5.8}$$

5.1.2 Recentered-influence functions

As our distributional statistics of interest are Gini index, quantiles, and interquantile ranges, a transformation of the outcome is required before the implementation of the "reweighted-regression" decomposition technique. The recentered influence function (RIF) of an outcome variable was proposed by Firpo et al. (2009) to evaluate the impact of changes in the distribution of the predictors on quantiles of the unconditional distribution of the outcome variable. The influence function *IF(y; v, F)* of a distributional statistic *v(F)* tells us how much an individual observation affects that distributional statistic (Firpo et al., 2009). The *RIF(y; v, F)* is then created by adding the statistic *v(F)* to *IF(y; v, F)* so that the expectation of *IF(y; v, F)* is equal to the statistic *v(F).*

The Gini index, quantiles, and interquantile ranges have the following RIF (Firpo et al., 2018):

Gini index v^G :

$$RIF(y; v^G, F_Y) = 1 + \frac{2}{\mu_Y^2} R(F_Y) - \frac{2}{\mu_Y}[y(1 - F_Y(y))]$$

where $R(F_Y) = \int_0^1 GL(p; F_Y)dp$, with $p(y) = F_Y(y)$ and $GL(p; F_Y) = \int_{-\infty}^{F^{-1}(p)} zdF_Y(z)$.

Quantile $q_Y(p)$:

$$\text{RIF}\ (y; q_Y(p), F_Y) = q_Y(p) + \frac{p - 1(y \leq q_Y(p))}{f(q_Y(p))}$$

Interquantile $iqr_Y(p_1, p_2)$:

$$\text{RIF}\ (y; iqr_Y(p_1, p_2), F_Y) = \text{RIF}\ (y; q_Y(p_1), F_Y) - \text{RIF}\ (y; q_Y(p_2), F_Y)$$

Other distributional statistics and the corresponding RIF are listed in Rios Avila (2019), together with the related literature for reference.

5.1.3 Detailed RIF decomposition model

At the first stage, we run a logit regression of membership status on the following vector of covariates:

X = {Education, RTI, Age, Gender, Public/Private, Coastal region, Industry}

and estimate the reweighting factor in Equation 5.5 to construct to counterfactual.

At the second stage, we regress the RIF of our inequality measures on the vector of covariates of the three groups: Group 0 (period 0), Group 1 (period 1), and the counterfactual Group *C*.

Finally, we decompose the changes in overall indices into total composition and total earnings structure effect, as in Equation (5.6), then further into detailed composition and detailed earnings structures effect, as in Equations (5.7) and (5.8).

Among our covariates, only RTI and age are continuous, the others are categorical. As noted by Jann (2008) and Firpo et al. (2011), the total contribution of a categorical variable to the total earnings structure effect varies according to the choice of the omitted based category. The difference will be transferred into the intercept (unobserved characteristics). Although some methods have been proposed to make the earnings structure effects of a categorical variable invariant, they are still somewhat arbitrary or make it difficult to interpret the size of the effects. Since the earnings inequality in Tunisia declines overtime, we choose to omit the most favored category, so that any increase in its returns, which increases earnings inequality, is interpreted as the result of the individual's unobserved characteristics. More precisely, we take male, public, coastal region and Hotels-Restaurant as based category. In the case of education, we take the secondary level as based category according to the common practice in the literature. The descriptive statistics of the covariates are presented in Table 5.1.

Table 5.1: Descriptive statistics of covariates

	2000	2010	2017
RTI	0.52	0.55	0.50
Age	35.23	36.46	37.95
Male=0 (Female)	0.60	0.56	0.51
Public=0 (Private)	70.98	73.33	74.75
Coast=0 (Inland)	33.16	34.74	33.34
Education			
No schooling	11.22	6.66	6.72
Primary	38.88	33.45	33.16

Secondary	37.28	39.81	38.79
Tertiary	12.62	20.08	21.33
Industry			
Agriculture	9.92	6.21	8.36
Mining	1.05	0.74	0.64
Manufacturing	21.84	23.23	21.79
Utilities	1.03	0.78	0.8
Construction	16.55	18.69	17.08
Wholesale & Retail	7.17	7.18	9.35
Hotels & Restaurant	4.24	4.82	4.24
Transport & Storage	5.22	5.66	4.71
Finance	1.56	1.23	1.36
Real estate	1.53	2.41	3.04
Public administration	12.74	10.94	11.15
Education	10.28	10.58	9.92
Healthcare	3.46	3.80	4.22
Other services	2.31	2.61	2.08
Private households	1.02	1.05	1.19
NGOs	0.10	0.07	0.08
Observations	20,046	100,909	89,159

5.2 Results

5.2.1 RIF regressions

Table 5.2 presents the OLS regressions of RIF of the Gini index on the covariates. The RTI level is negatively correlated with inequality. This is consistent with the logic of the routinization hypothesis and its consequent polarization: the more the RTI level reduces, the more polarized the wage distribution will be. As for education, an increase in employment share of no schooling, primary- or tertiary-educated workers all contributes to increases in the overall inequality but in the different ways: the expansion of the first two worker categories brings down the lower half of the earnings distribution, while the expansion of tertiary-educated workers' share elevates the upper half of the earnings distribution. For other factors, an increase in the employment share of private sector, female workers or workers in coastal areas are related to increases in the Gini coefficient.

Table 5.2: RIF regressions with Gini index

	Gini					
	2000		2010		2017	
RTI	-0.036***	(0.006)	-0.069***	(0.003)	-0.058***	(0.003)

Age	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Public=0	0.087***	(0.015)	0.02**	(0.009)	0.037***	(0.013)
Coast=0	0.053***	(0.006)	0.034***	(0.002)	0.012***	(0.003)
Education						
No schooling	0.063***	(0.01)	0.031***	(0.003)	0.023***	(0.005)
Primary	0.042***	(0.006)	0.013***	(0.002)	0.002	(0.003)
Tertiary	0.264***	(0.018)	0.188***	(0.006)	0.151***	(0.009)
Industry						
Agriculture	0.233***	(0.012)	0.137***	(0.005)	0.088***	(0.006)
Mining	0.17***	(0.05)	0.268***	(0.023)	0.128***	(0.025)
Manufacturing	0.05***	(0.013)	0.069***	(0.005)	0.059***	(0.007)
Utilities	0.042**	(0.02)	0.114***	(0.015)	0.156***	(0.05)
Construction	0.116***	(0.012)	0.099***	(0.005)	0.039***	(0.006)
Wholesale & Retail	0.081***	(0.014)	0.045***	(0.005)	0.043***	(0.006)
Transport & ICT	0.073***	(0.014)	0.078***	(0.007)	0.074***	(0.009)
Finance	0.151***	(0.044)	0.306***	(0.033)	0.368***	(0.045)
Real estate	0.089***	(0.029)	0.031***	(0.011)	0.039***	(0.014)
Public administration	0.087***	(0.017)	0.038***	(0.01)	0.089***	(0.013)
Education	-0.02	(0.019)	-0.037***	(0.012)	0.085***	(0.015)
Healthcare	0.07***	(0.026)	0.024*	(0.013)	0.057***	(0.017)
Other services	0.167***	(0.035)	0.14***	(0.011)	0.153***	(0.053)
Private households	0.125**	(0.05)	0.094***	(0.013)	0.067***	(0.016)
NGOs	0.6*	(0.332)	0.105	(0.103)	0.088	(0.07)
Constant	0.128***	(0.021)	0.212***	(0.01)	0.198***	(0.013)
Observations	15 090		68 221		44 346	
F-statistic	83.17		292.65		191.66	
Prob > F	0.000		0.000		0.000	
R-squared	0.1268		0.1647		0.1858	
Root MSE	0.296		0.242		0.216	

Robust standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1.

5.2.2 RIF decomposition

The results of the Gini's RIF decomposition are presented in Table 5.3. Although more than half of the specification errors, which measure the importance of departures from the linearity assumption (Firpo et al., 2018), are significant, they are relatively small when compared to the total changes of the distribution. Furthermore, the reweighting errors are trivial, which means that the estimate of the reweighting factor is consistent. So, it can be said that the reweighting RIF decomposition model performs relatively well at estimating the composition and discrimination effects.

In general, the total composition effect contributed to increases in Gini coefficient during the first sub-period. However, the disequalizing composition effect was entirely counteracted by the equalizing wage structure effect. The two effects also had contrary trends: total composition effect tended to rise while the wage structure effect tended to fall overtime.

The composition effects were mostly induced by the change in education composition of the labor force. The increase in education attainment had a disequalizing effect (positive coefficient). This is similar to the finding of Ferreira et al. (2021) in Brazil's labor market and again confirms Bourguignon and Ferreira's "paradox of progress" (2005), where the convexity of education premium widened the earnings gap between college graduates and the rest. During the first sub-period, the increase of the private sector's share in the labor market also positively contributed to the overall inequality since wages were more equally paid in the public sector.

Moving to the detailed wage structure effects, we unexpectedly find that the most important factors are not skill supply but two demand-side factors: the public-private wage gap and the sector wage gap. The reduction in wage gap between public and private high-skilled workers was the largest contributor to the decline in earnings inequality over the last two decades. Most of the change in public–private wage gap took place in the first sub-period. No significant change is observed in the second sub-period. This finding is consistent with our previous analysis that the Revolution reversed the disequalizing trend of the public wage policy and made it similar to the equalizing trend of the market wage. The change in sector premium, mainly before 2011, was the second contributor to the reduction of the overall earnings inequality. The return-to-education decline, despite not being the most important, still contributed largely to the decrease of the Gini index. The smaller contribution of education to decreases in the Gini index after the Revolution corresponds to the smaller slope of education premium during this period. Among the covariates, only RTI had the contrary contributions over the two sub-periods. During the 2000–2010 period, the increase in marginal returns to low-wage but average-RTI jobs (the L-shape pattern of log earnings evolution in Section 4.2) enhanced the equality. In the second sub-period, RTI had a small enhancing-inequality effect. It is worth noting that during the same sub-period, we find that the falling return to experience (proxied by age) had a substantial contribution to the decline in earnings inequality. This effect of the age-biased technological change is observed in Brazil's labor market (Ferreira et al., 2021) as well.

Table 5.3: RIF decomposition of changes in the Gini index

	Gini					
	2000-2010		2010-2017		2000-2017	
Overall						
Final (F)	0.315***	(0.001)	0.295***	(0.001)	0.295***	(0.002)
Counterfactual (C)	0.359***	(0.003)	0.323***	(0.001)	0.37***	(0.003)
Initial (I)	0.355***	(0.003)	0.315***	(0.001)	0.355***	(0.002)
Total change (F-I)	-0.041***	(0.003)	-0.02***	(0.002)	-0.06***	(0.003)
Total composition (C-I)	0.004*	(0.002)	0.008***	(0.001)	0.014***	(0.002)
Total earnings structure (F-C)	-0.044***	(0.003)	-0.028***	(0.002)	-0.075***	(0.003)

RIF aggregate decomposition						
RIF composition	0.005***	(0.002)	0.007***	(0.001)	0.016***	(0.002)
RIF specification error	-0.002**	(0.001)	0.000***	(0.000)	-0.002**	(0.001)
RIF earnings structure	-0.044***	(0.003)	-0.028***	(0.002)	-0.076***	(0.003)
RIF reweighting errors	0.000	(0.000)	0.000	(0.000)	0.001**	(0.000)
RIF detailed decomposition						
RIF composition						
RTI	-0.002***	(0.000)	0.002***	(0.000)	-0.001	(0.000)
Age	0.000	(0.000)	0.000	(0.000)	0.000	(0.001)
Male=0	0.001***	(0.000)	0.001***	(0.000)	0.001***	(0.000)
Public=0	0.003***	(0.001)	0.000***	(0.000)	0.004***	(0.001)
Coast=0	0.001**	(0.000)	0.001***	(0.000)	0.002***	(0.000)
Education	0.009***	(0.001)	0.001***	(0.000)	0.009***	(0.001)
Industry	-0.006***	(0.001)	0.003***	(0.000)	0.000	(0.001)
RIF Earnings structure						
RTI	-0.017***	(0.004)	0.005***	(0.002)	-0.013***	(0.003)
Age	-0.014	(0.012)	-0.018***	(0.006)	-0.024*	(0.012)
Male=0	0.004*	(0.002)	0.003**	(0.001)	0.008***	(0.003)
Public=0	-0.052***	(0.016)	-0.002	(0.008)	-0.054***	(0.015)
Coast=0	-0.004*	(0.003)	-0.008***	(0.001)	-0.014***	(0.002)
Education	-0.021***	(0.003)	-0.013***	(0.002)	-0.035***	(0.004)
Industry	-0.028**	(0.011)	-0.011*	(0.006)	-0.04***	(0.01)
Intercept	0.089***	(0.027)	0.017	(0.012)	0.096***	(0.026)

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

The decomposition of change in the Gini index provides a big picture of the total contribution of each factor to the total change of the distribution. However, it is silent about how these factors affected the earnings distribution, for example, which factor levelled up the lower end of the distribution, which factor pulled down the upper end of the distribution, etc. Therefore, we also look at the impact of each factor at the percentile level. The results are shown in Figure 5.1 and Figure 5.2. The total decomposition results in Figure 5.1 are consistent with the Gini decomposition. The changes in log earnings were mostly explained by the changes in the earnings structure of the percentiles. The adverse composition effects were completely counterbalanced by the earnings structure effects in both sub-periods.

In terms of composition effects, we can see that those who benefited the most from education expansion were the employees in high-paid jobs, especially during the first sub-period. Other factors had relatively small composition effect in comparison to the effects of education.

In terms of structural effects, the reduction in wage gap between private and public sector was mostly driven by the reduction in the upper half of the distribution. Meanwhile, the structural changes reduced the overall inequality by upgrading the industrial premium of the low-skilled jobs during the first sub-period and the industrial premium of the middle-skilled jobs during the second sub-period. The downward-sloping curve of education's earnings structure effects is also in line with the decline in education premium of all schooling levels comparing to the no-schooling level.

For a robustness check, we run the same decomposition with the p90/p50 and p50/p10 ranges, as well as with different data sets, including a data set with imputed earnings for missing observations and the subset of male workers. The results (presented in the Appendix) are consistent with the above results of Gini and percentile decomposition using the original data set.

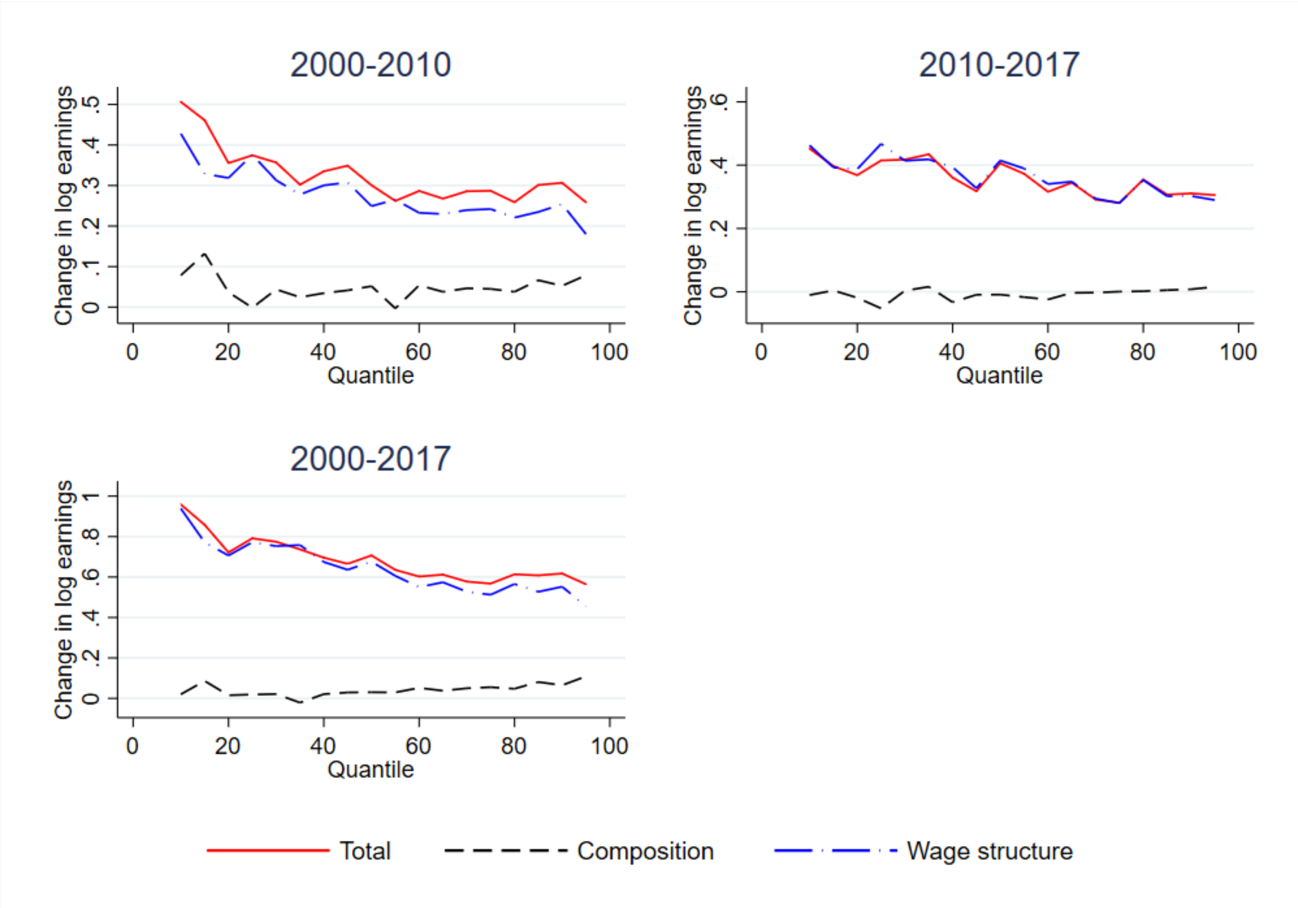

Figure 5.1: RIF decomposition of total earnings change into wage structure and composition effects

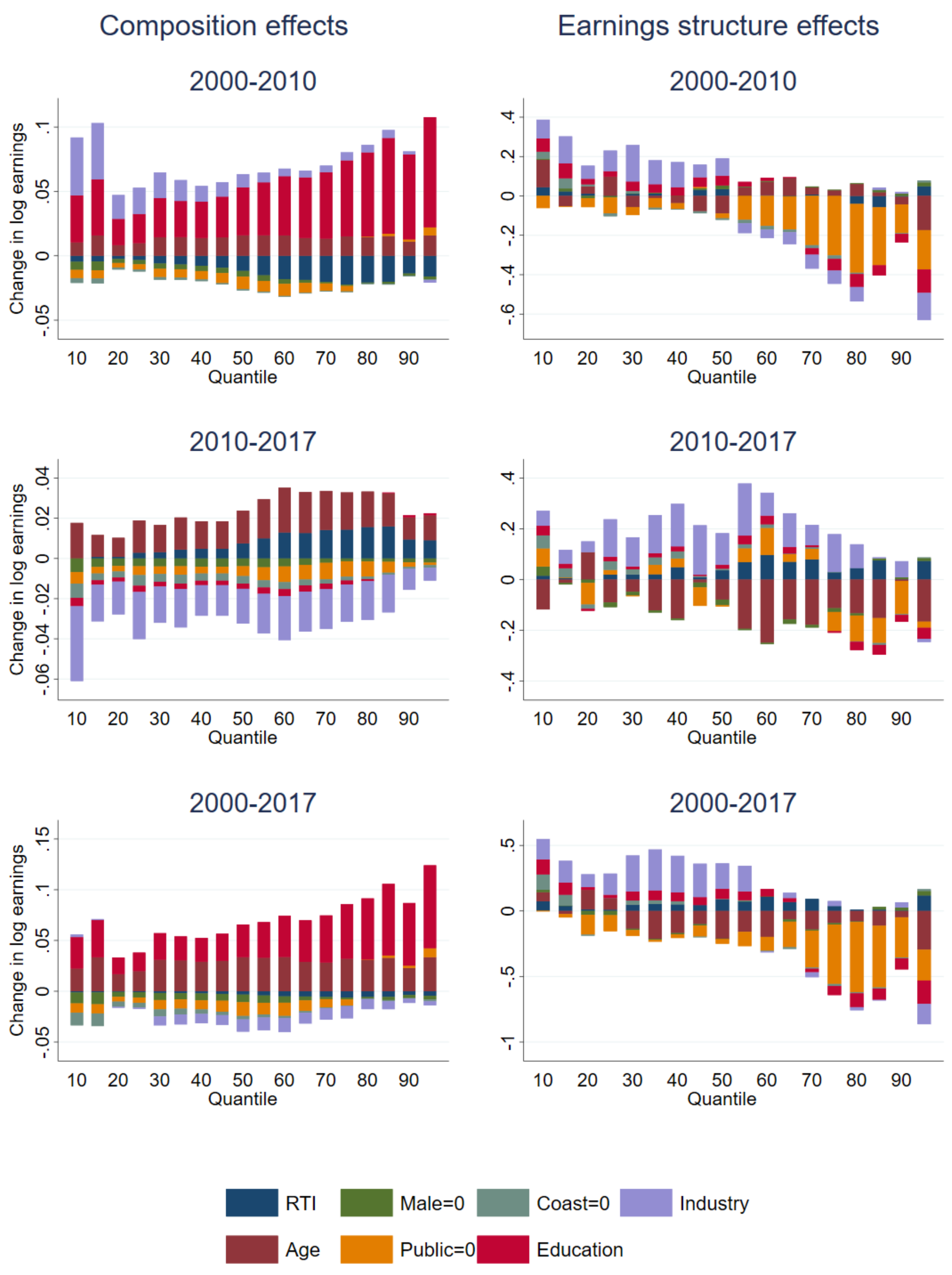

Figure 5.2: Detailed RIF decomposition of determinants of earnings changes

6 Conclusion

Over the last two decades, Tunisia's labor market experienced a strong decline in earnings inequality. The dynamic of earnings followed an L-shape polarization with higher earnings growth concentrated at the lower end of the distribution, a pattern that has been also observed in China. Four main factors of the inequality variations were identified: skill supply, technological changes, structural changes, and public wage and employment policies.

Similar to other MENA countries, Tunisia witnessed a downward trend of skill premia due to the excess supply of tertiary-educated job seekers. On the demand side, we first investigated the role of routine-biased technical changes and find ambiguous evidence. While the L-shape wage polarization points out to the Routine-biased technical changes, the positive linear correlation between earnings and RTI put a question mark over its role. On the contrary, we observed strong declining trends of sector premia and the public–private wage gap, which are congruent with the change in overall earnings inequality. The outflow of labor from agriculture and manufacturing due to service-led deindustrialization resulted in favorable earnings changes to agricultural and manufacturing jobs, especially elementary jobs in these sectors. Whereas the wage gap between private and public sectors fell sharply during the pre-Revolution period, it hardly changed after that since the public wage dynamic became similar to the private wage dynamic.

Our RIF decomposition of earnings inequality changes showed that the overall change was mostly driven by the earnings structure effects. In terms of composition effects, the effect of education is dominant and disequalizing. In terms of earnings structure effects, the main contributors are decreases in the public–private wage gap and sector wage gap on the demand side and the decreasing education premia on the supply side. The increase in marginal returns to low-wage but average-RTI jobs, the falling return to experience, and the decreasing regional wage gap are also found to have contributed to the decline in overall earnings inequality.

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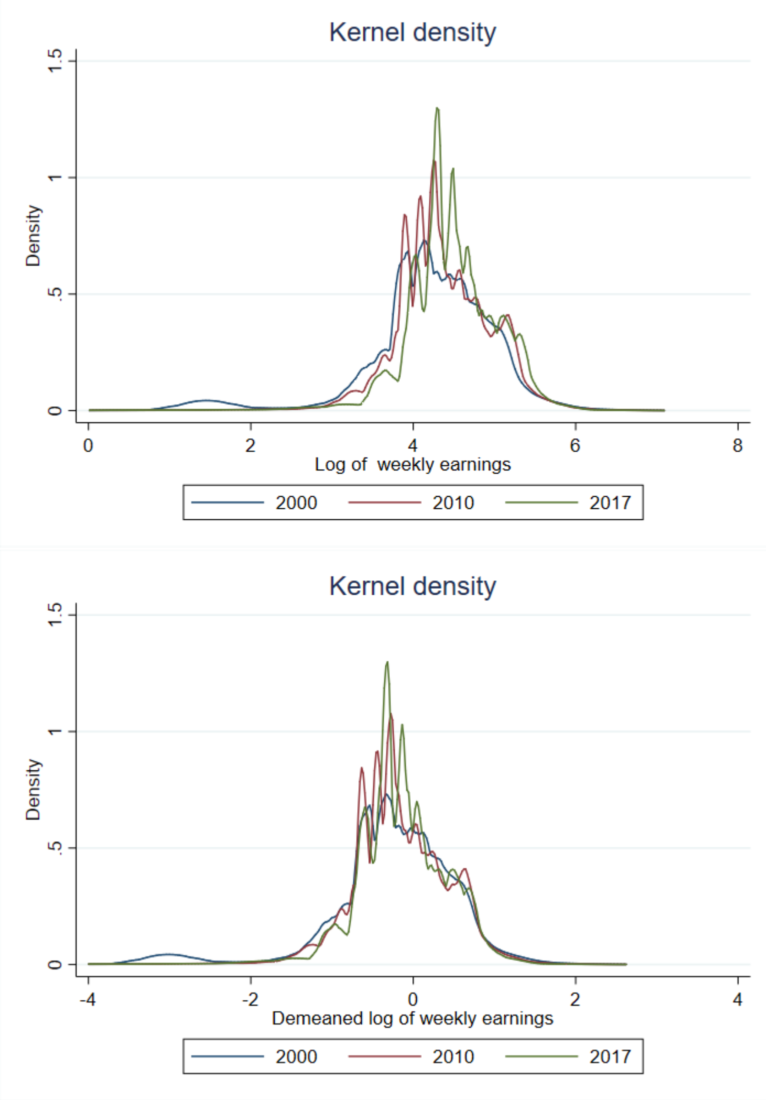
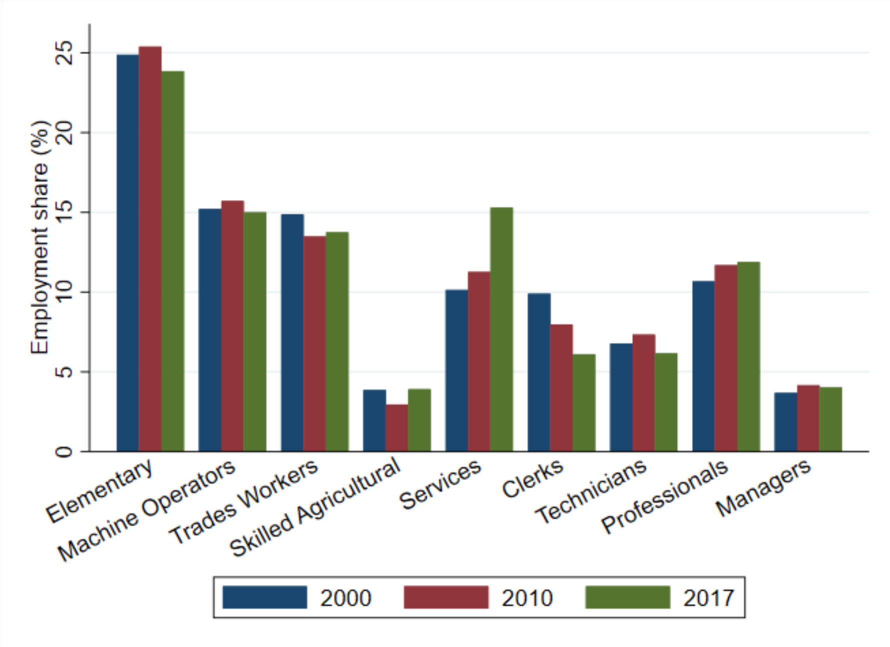
A Appendix

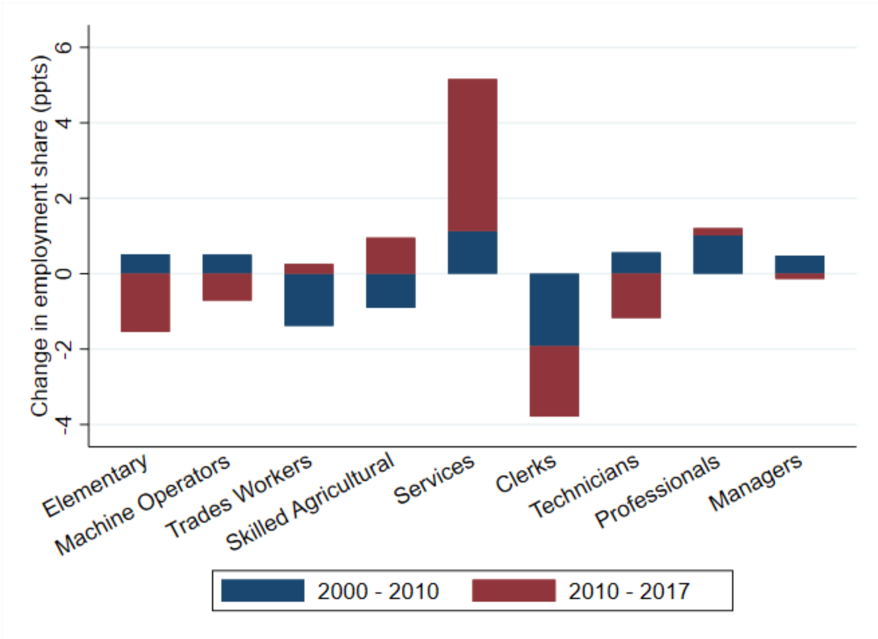
A.3 A decrease in inequality over the two decades



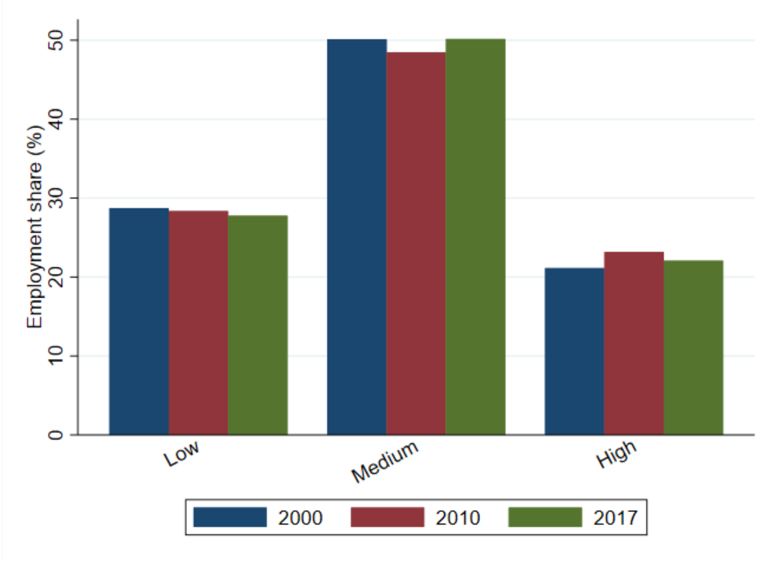
Appendix Figure A.3.1: Adaptive kernel densities



Appendix Figure A.3.2: Employment share by occupational group



Appendix Figure A.3.3: Change in employment share by occupational group



Appendix Figure A.3.4: Employment share by skill level

Appendix Table A.3.1: Employment shares by 3-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	Protective services workers	2.31	2.84	3.75
523	Stall and market salespersons	0.46	0.23	0.30

A.4 Underlying factors of the inequality trend

Appendix Table A.4.1: 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
F-test	0.631	0.0741	0.134	0.000	0.000	0.000

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

Appendix Table A.4.2: 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
F-test	0.758	0.0179	0.324	0.000	0.000	0.000

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

Appendix Table A.4.3: 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
F-test	0.252	0.312	0.075	0.000	0.000	0.000

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

Appendix Table A.4.4: 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
F-test	0.000	0.03	0.021	0.000	0.000	0.000

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

A.5 Decomposition of inequality decline

Appendix Table A.5.1: RIF regressions with p50/p10 ratio

	p50/10					
	2000		2010		2017	
RTI	-0.12***	(0.016)	-0.197***	(0.006)	-0.149***	(0.005)
Age	0.005***	(0.001)	-0.001***	(0.000)	0.002***	(0.000)
Male=0	0.072***	(0.027)	0.104***	(0.009)	-0.023**	(0.009)
Public=0	-0.086*	(0.046)	0.049**	(0.019)	-0.086***	(0.016)
Coast=0	0.257***	(0.025)	0.129***	(0.007)	-0.043***	(0.007)
Education (Secondary=0)						
No schooling	0.085	(0.054)	0.18***	(0.019)	0.037**	(0.018)
Primary	-0.028	(0.028)	0.044***	(0.01)	-0.063***	(0.009)
Tertiary	0.048***	(0.019)	-0.049***	(0.009)	0.078***	(0.01)
Industry (Hotel & Restaurant=0)						
Agriculture	0.701***	(0.073)	0.765***	(0.027)	0.234***	(0.023)
Mining	0.145*	(0.076)	0.336***	(0.032)	0.44***	(0.031)
Manufacturing	-0.062	(0.05)	0.037**	(0.018)	0.169***	(0.02)
Utilities	0.125*	(0.073)	0.356***	(0.031)	0.467***	(0.028)
Construction	-0.202***	(0.056)	0.047***	(0.018)	0.273***	(0.02)
Wholesale & Retail	-0.001	(0.061)	0.159***	(0.022)	0.165***	(0.023)
Transport & ICT	0.239***	(0.061)	0.309***	(0.019)	0.283***	(0.023)
Finance	0.219***	(0.055)	0.292***	(0.024)	0.309***	(0.034)
Real estate	-0.231***	(0.077)	0.094***	(0.03)	0.219***	(0.028)
Public administration	0.182***	(0.065)	0.437***	(0.026)	0.27***	(0.024)
Education	-0.005	(0.065)	0.148***	(0.026)	0.137***	(0.025)
Healthcare	0.08	(0.071)	0.268***	(0.029)	0.224***	(0.03)
Other services	0.3***	(0.108)	0.493***	(0.036)	0.218***	(0.033)

Private households	0.556***	(0.197)	0.517***	(0.058)	0.08	(0.052)
NGOs	0.178	(0.163)	0.238**	(0.094)	0.069	(0.103)
Constant	0.577***	(0.078)	0.422***	(0.029)	0.437***	(0.028)
Number of obs	19,642		92,612		60,152	
F-statistic	62.430		494.350		301.170	
Prob > F	0.000		0.000		0.000	
R-squared	0.066		0.102		0.092	
Root MSE	1.407		0.993		0.671	

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

Appendix Table A.5.2: RIF regressions with p90/p50 ratio

	p90/50					
	2000		2010		2017	
RTI	-0.054***	(0.016)	-0.053***	(0.006)	-0.136***	(0.008)
Age	-0.003***	(0.001)	-0.004***	(0.000)	-0.001**	(0.000)
Male=0	0.1***	(0.021)	0.071***	(0.008)	0.161***	(0.012)
Public=0	0.316***	(0.042)	0.146***	(0.017)	-0.006	(0.026)
Coast=0	0.08***	(0.015)	0.097***	(0.006)	0.067***	(0.008)
Education						
No schooling	0.356***	(0.024)	0.213***	(0.009)	0.113***	(0.014)
Primary	0.256***	(0.017)	0.111***	(0.006)	0.055***	(0.009)
Tertiary	0.979***	(0.043)	0.463***	(0.014)	0.415***	(0.02)
Industry						
Agriculture	0.676***	(0.036)	0.365***	(0.013)	0.252***	(0.019)
Mining	0.274***	(0.092)	0.608***	(0.049)	0.128*	(0.075)
Manufacturing	0.323***	(0.041)	0.194***	(0.015)	0.174***	(0.022)
Utilities	0.197**	(0.092)	0.222***	(0.048)	0.108	(0.081)
Construction	0.522***	(0.04)	0.136***	(0.015)	0.017	(0.02)
Wholesale & Retail	0.332***	(0.043)	0.119***	(0.015)	0.058***	(0.022)
Transport & ICT	0.197***	(0.051)	0.011	(0.02)	0.068**	(0.032)
Finance	0.479***	(0.104)	0.679***	(0.049)	0.702***	(0.093)
Real estate	0.434***	(0.079)	0.083***	(0.025)	-0.074*	(0.042)
Public	0.24***	(0.055)	-0.025	(0.022)	-0.022	(0.032)

administration						
Education	0.205***	(0.063)	0.314***	(0.025)	0.499***	(0.037)
Healthcare	0.024	(0.064)	-0.154***	(0.023)	-0.25***	(0.034)
Other services	0.406***	(0.066)	0.28***	(0.02)	0.098**	(0.044)
Private households	0.614***	(0.053)	0.38***	(0.018)	0.342***	(0.028)
NGOs	1.169**	(0.466)	-0.095	(0.183)	0.563*	(0.336)
Constant	0.085	(0.06)	0.533***	(0.023)	0.539***	(0.034)
Number of obs	19,642		92,612		60,152	
F-statistic	150.510		389.100		224.660	
Prob > F	0.000		0.000		0.000	
R-squared	0.150		0.104		0.160	
Root MSE	0.907		0.780		0.857	

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

Appendix Table A.5.3: RIF decomposition of changes in the p50/p10 and p90/p50 ratios

	p50/p10				p90/p50			
	2000-10		2010-17		2000-10		2010-17	
Overall								
Final (F)	0.589***	(0.003)	0.542***	(0.003)	0.825***	(0.005)	0.73***	(0.009)
Counterfactual (C)	0.768***	(0.015)	0.589***	(0.004)	0.82***	(0.01)	0.842***	(0.005)
Initial (I)	0.794***	(0.018)	0.589***	(0.009)	0.82***	(0.009)	0.825***	(0.005)
Total change (F-I)	-0.205***	(0.018)	-0.046***	(0.009)	0.005	(0.011)	-0.095***	(0.01)
Total composition (C-I)	-0.026	(0.016)	0.000	(0.009)	0.001	(0.012)	0.017***	(0.004)
Total earnings structure (F-C)	-0.179***	(0.016)	-0.047***	(0.005)	0.005	(0.012)	-0.112***	(0.009)
RIF aggregate decomposition								
RIF composition	-0.034***	(0.006)	0.035***	(0.003)	0.034***	(0.006)	0.014***	(0.002)
RIF specification error	0.008	(0.014)	-0.035***	(0.011)	-0.033***	(0.012)	0.003	(0.004)
RIF earnings structure	-0.174***	(0.016)	-0.046***	(0.005)	0.003	(0.012)	-0.114***	(0.009)
RIF reweighting errors	-0.005***	(0.001)	-0.001***	(0.000)	0.002**	(0.001)	0.002***	(0.000)
RIF detailed decomposition								
RIF composition								
RTI	-0.007***	(0.002)	0.008***	(0.001)	-0.003**	(0.001)	0.002***	(0.000)

Age	0.005***	(0.002)	-0.001**	(0.001)	-0.004***	(0.001)	-0.005***	(0.001)
Male=0	0.002**	(0.001)	0.003***	(0.001)	0.003***	(0.001)	0.002***	(0.000)
Public=0	-0.003	(0.002)	0.001*	(0.000)	0.011***	(0.002)	0.003***	(0.000)
Coast=0	0.003**	(0.001)	0.003***	(0.001)	0.001**	(0.000)	0.003***	(0.000)
Education	0.001	(0.004)	0.002***	(0.000)	0.034***	(0.005)	0.004***	(0.001)
Industry	-0.035***	(0.003)	0.02***	(0.003)	-0.008***	(0.003)	0.007***	(0.001)
RIF earnings structure								
RTI	-0.017	(0.013)	0.022***	(0.006)	-0.023*	(0.013)	-0.034***	(0.008)
Age	-0.209***	(0.061)	0.05**	(0.02)	0.006	(0.037)	0.073***	(0.021)
Male=0	0.012	(0.009)	-0.062***	(0.004)	-0.002	(0.007)	0.031***	(0.004)
Public=0	0.032	(0.041)	-0.084***	(0.022)	-0.116**	(0.049)	-0.126***	(0.025)
Coast=0	-0.043***	(0.01)	-0.047***	(0.004)	0.007	(0.007)	-0.01**	(0.004)
Education	-0.02	(0.018)	-0.024***	(0.006)	-0.097***	(0.013)	-0.044***	(0.008)
Industry	-0.006	(0.053)	0.06**	(0.025)	-0.089*	(0.046)	-0.063***	(0.023)
Intercept	0.077	(0.091)	0.04	(0.042)	0.316***	(0.091)	0.06	(0.039)

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

Appendix Table A.5.4: RIF decomposition of changes in Gini index - Male employees

	Gini					
	2000-2010		2010-2017		2000-2017	
Overall						
Final (F)	0.306***	(0.001)	0.275***	(0.002)	0.275***	(0.002)
Counterfactual (C)	0.356***	(0.004)	0.311***	(0.001)	0.366***	(0.004)
Initial (I)	0.356***	(0.003)	0.306***	(0.001)	0.356***	(0.003)
Total change (F-I)	-0.051***	(0.003)	-0.031***	(0.002)	-0.082***	(0.003)
Total composition (C-I)	0.000	(0.003)	0.005***	(0.001)	0.009***	(0.003)
Total earnings structure (F-C)	-0.051***	(0.004)	-0.036***	(0.002)	-0.091***	(0.004)
RIF aggregate decomposition						
RIF composition	0.000	(0.002)	0.005***	(0.001)	0.009***	(0.002)
RIF specification error	0.000	(0.001)	0.000	(0.000)	0.000	(0.001)
RIF earnings structure	-0.051***	(0.003)	-0.036***	(0.002)	-0.092***	(0.004)
RIF reweighting errors	0.000	(0.000)	0.000	(0.000)	0.001**	(0.000)
RIF detailed decomposition						
RIF composition						
RTI	-0.004***	(0.001)	0.003***	(0.000)	-0.002***	(0.001)
Age	0.001*	(0.000)	0.000	(0.000)	0.001	(0.001)
Public=0	0.003***	(0.001)	0.000**	(0.000)	0.005***	(0.001)
Coast=0	0.000	(0.000)	0.001***	(0.000)	0.002***	(0.000)
Education	0.007***	(0.001)	-0.002***	(0.000)	0.003**	(0.001)
Industry	-0.007***	(0.001)	0.003***	(0.000)	0.000	(0.001)
RTI	-0.023***	(0.006)	0.008***	(0.002)	-0.015***	(0.004)
Age	-0.023	(0.017)	-0.019**	(0.008)	-0.034**	(0.016)
Public=0	-0.066***	(0.022)	0.012	(0.011)	-0.053***	(0.02)
Coast=0	-0.004	(0.002)	-0.01***	(0.001)	-0.015***	(0.003)
Education	-0.02***	(0.004)	-0.012***	(0.003)	-0.033***	(0.005)
Industry	-0.028**	(0.011)	-0.007	(0.008)	-0.034***	(0.012)
Intercept	0.112***	(0.039)	-0.008	(0.015)	0.093***	(0.032)

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

Appendix Table A.5.5: RIF decomposition of changes in Gini index - Imputed data

	Gini					
	2000-2010		2010-2017		2000-2017	
Overall						
Final (F)	0.324***	(0.001)	0.319***	(0.001)	0.319***	(0.001)
Counterfactual (C)	0.362***	(0.003)	0.33***	(0.001)	0.369***	(0.004)
Initial (I)	0.358***	(0.002)	0.324***	(0.001)	0.358***	(0.002)
Total change (F-I)	-0.035***	(0.002)	-0.005***	(0.002)	-0.04***	(0.003)
Total composition (C-I)	0.004*	(0.002)	0.007***	(0.001)	0.011***	(0.002)
Total earnings structure (F-C)	-0.039***	(0.003)	-0.012***	(0.002)	-0.051***	(0.004)
RIF aggregate decomposition						
RIF composition	0.007***	(0.002)	0.006***	(0.001)	0.014***	(0.002)
RIF specification error	-0.003***	(0.001)	0.000**	(0.000)	-0.003***	(0.001)
RIF earnings structure	-0.038***	(0.003)	-0.012***	(0.002)	-0.052***	(0.004)
RIF reweighting errors	0.000	(0.000)	0.000	(0.000)	0.001***	(0.000)
RIF detailed decomposition						
RIF composition						
RTI	-0.001*	(0.000)	0.003***	(0.000)	0.002***	(0.000)
Age	0.000	(0.000)	0.000	(0.000)	0.001	(0.001)
Public=0	0.000***	(0.000)	0.000***	(0.000)	0.001***	(0.000)
Coast=0	0.002***	(0.000)	0.000	(0.000)	0.002***	(0.001)
Education	0.001***	(0.000)	0.000***	(0.000)	0.000	(0.000)
Industry	0.01***	(0.002)	0.001***	(0.000)	0.011***	(0.001)
RIF Specification errors						
RTI	-0.015***	(0.004)	0.008***	(0.001)	-0.007**	(0.003)
Age	-0.009	(0.014)	-0.005	(0.006)	-0.007	(0.015)
Public=0	0.003	(0.002)	0.000	(0.001)	0.005*	(0.002)
Coast=0	-0.065***	(0.013)	-0.013*	(0.007)	-0.077***	(0.014)
Education	-0.005**	(0.002)	-0.009***	(0.001)	-0.014***	(0.002)
Industry	-0.02***	(0.003)	-0.019***	(0.002)	-0.039***	(0.004)
Intercept	-0.034***	(0.012)	-0.026***	(0.006)	-0.059***	(0.01)

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