Jobs, earnings and routine-task occupational change in times of Revolution : The Tunisian perspective

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Abstract

The objective of this paper is to investigate the links between earnings inequality and the changing nature of jobs in a revolution context. The methodology consists of various decompositions and regressions based on Tunisian labour force surveys from the past 20 years. Tunisa's labor market during the period of investigation is characterized by a decreasing earnings inequality following the fall of education premia, and an asymmetric wage polarization mainly led by the increase of the lowest wages. When we remove the public sector, we end up with job polarization and wage polarization only before the Revolution, which confirms the impact of the public sector on inequality in the Revolution era. 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 crowd out by employment and wage policies in the public sector.

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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-nineties to the global crisis (5%). In the last twenty years the youth unemployment has been severe, particularly for graduates (between 30 and 40% according to Asik et al. (2020)). 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 leaving a long lasting impact on the whole Middle-East and North Africa 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 rebellions (Urdal, 2006; Nordås and Davenport, 2013). The objective of this research is to analyze the role played by the evolution of the nature of jobs in the dynamics of earnings distribution in the decades preceding and following the Revolution. Our aim is also to identify regularities and changes that may have occurred due to the Tunisian Revolution or to structural factors such as demography. Much of the academic literature on employment and wage distribution focuses on levels of education, suggesting that the allocation of skills is the strongest determinant of labor market outcomes. However an 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.

The literature on rich countries has shown that the evolution of occupations and tasks over time is a key determinant in understanding jobs and wage polarization. According to the literature that uses 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.

Studying the case of Portugal, a country with slow adoption of automation, Fonseca et al. (2018) show that the decline of routine manual tasks jobs is the main determinant of job and wage polarization, while routine cognitive tasks jobs do not witness a similar outcome. Lewandowski et al. (2019) tests 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) investigate also 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 United States, long before the ICT revolution. Their analysis is based on the complementarity between consumption goods in manufacturing (intensive in medium skilled workers), low-skill and high-skill services and on 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 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 in 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 in between and within-occupations inequality. 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 to 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. The second result is that Tunisia has witnessed a shift towards jobs demanding high skills until the Revolution, then the movement was reversed. Moreover, a wage polarization is highlighted, but unlike developed countries, Tunisian polarization seems to have been mainly led by the increase of the lowest wages, similarly 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 being 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

The data used for this paper is 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 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 time conducted in 2000 in order 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 households, including gender, age, relationship with the householder, marital position, education, working status and the 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.

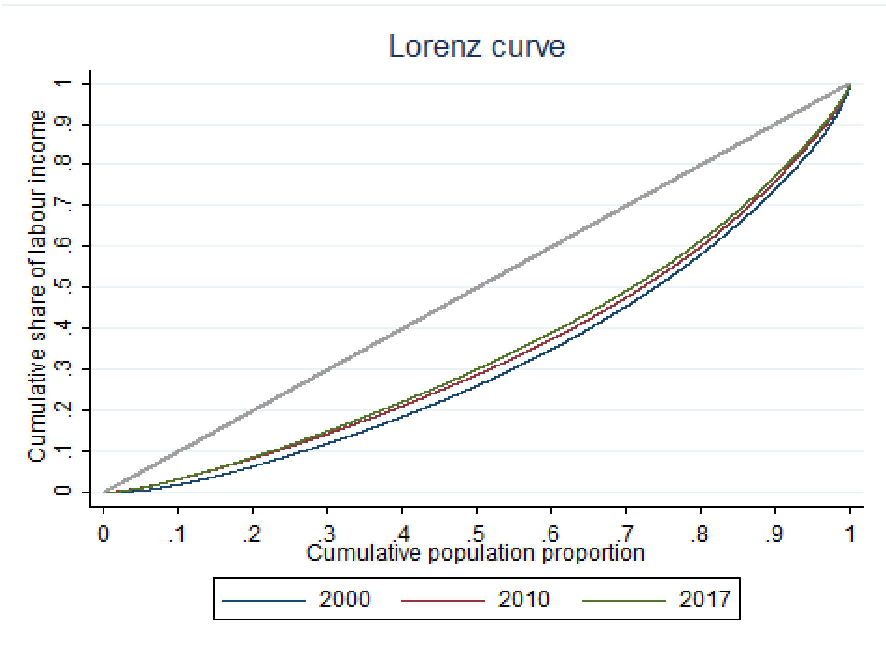
Among the three waves of survey to which we have access, two waves (2000 and 2010) use NNP97 (National Nomenclature of Professions – 1997), corresponding to ISCO-88 and the third one in 2017 uses NNP-14, corresponding to ISCO-08. Therefore, we firstly mapped NNP to the corresponding ISCO, then ISCO-08 to ISCO-88. 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 were classified as skilled workers (group 61, ISCO-88). 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. We observed that the supervisors in ISCO-08 (occupations 3121 - mining supervisors, 3122 - manufacturing supervisors and 3123 - construction supervisors) were classified as workers, assemblers or operators in ISCO-88 (occupations 81XX). Given that most of these supervisor jobs are rather non-routine tasks than routine tasks, putting them among the routine jobs can be problematic. Therefore, we recoded the supervisors into occupations 1312 and 1313 - general managers, using earnings distribution and other features relating to the position, such as workplace, contract types and payment methods. Since occupations were precisely recorded at the 4- or 5-digit level, eventually, we were able to create a cross-sectional data set with task-measure indices at the 4-digit-ISCO-88 level.

3 Changes in job distribution and earnings inequality

3.1 General trends

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 period witnesses a rapid fall in earnings inequality, the Gini index dropped by 4 percentage points over ten years. This reduction halved to around 2 percentage points in the second period. The Lorenz curves in Figure 3.1 provide an illustration of these trends.

Figure 3.1: Lorenz curves



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 the same way. On a macro level, we see that the variance in earnings may have fallen considerably from 2000 to

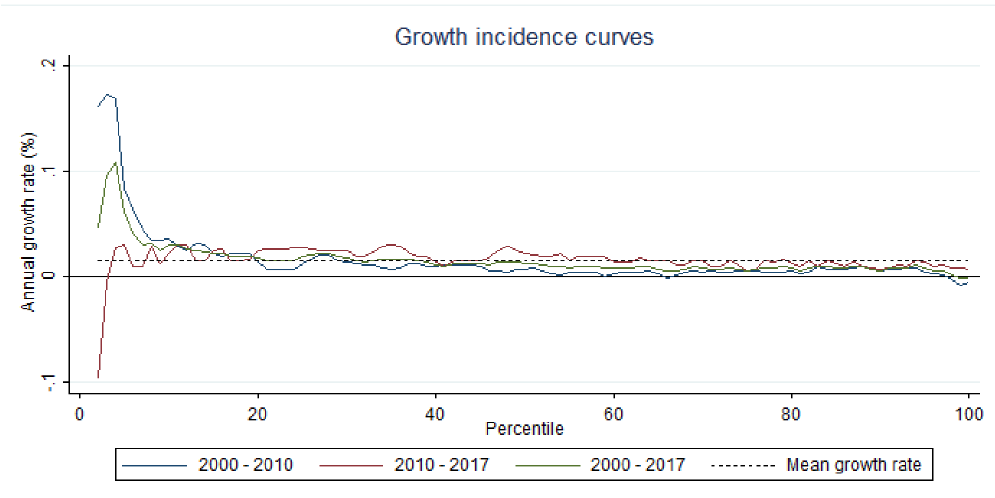
Table 3.1: Summary inequality indices and Inter-quantile ratios

Summary indices				Inter-quantile ratios			
	2000	2010	2017		2000	2010	2017
Var (log)	0.638	0.393	0.491	ln(q90)-ln(q10)	1.624	1.408	1.256
Gini (log)	0.098	0.073	0.068	ln(q90)-ln(q50)	0.835	0.832	0.745
Gini	0.353	0.312	0.294	ln(q50)-ln(q10)	0.788	0.575	0.511

2010, but this improvement was followed by an increase in 2017 as compared to 2010. In fact, the difference between earnings in the bottom 50^{th} (median) to 10^{th} percentiles decreased more than those in the top 90^{th} to 50^{th} percentile (Table 3.1). The earnings gap between the 90^{th} and 50^{th} percentiles narrowed mostly during the post-revolution period, whereas the earnings gap between the 90^{th} and 10^{th} 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 earners.

Examining the earning growth by percentile (Figure 3.2), 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 to 2017 period. We also see opposite patterns for high end earners confirming that 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 out by growth in middle-wage occupations.

Figure 3.2: Growth incidence curves of the wage distribution

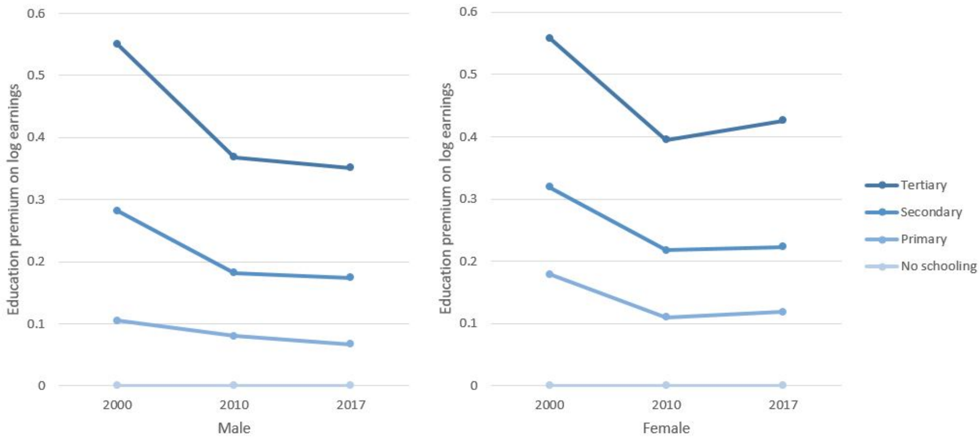


The decreasing trends of earnings inequality were in congruence with the substantial decline in the education premium. While the supply of highly educated workers was and remained high, the demand for jobs in more productive and high earnings sectors stagnated (Marouani and Mouelhi, 2016). The unemployment rate of the Tunisian graduates soared from 10.4 percent in 2001 to 22.9 percent in 2010[1] and 30 percent

[1]Adel, Bousnina, "Le chômage en Tunisie : les principales caractéristiques", Edition L'Harmattan, Paris, 2013, pp.45-75.

in 2017[2]. 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 earnings jobs decreased for both men and women (Figure 3.3). 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 reduced to 10 percentage points by 2017.

Figure 3.3: Change in the education premium on log labour earnings by gender



Although the education premium has been decreasing very sharply since 2000 (Figure 3.3), this movement slowed down for men and the movement was 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 leveled 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 Skills distributions

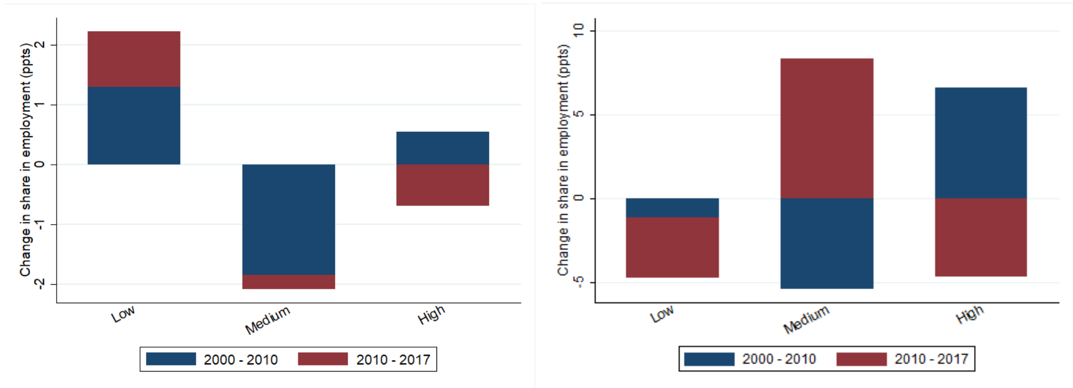
The trends in earnings inequality show some underlying heterogeneity. One of the reasons for these changes are the evolving share and earnings associated with occupations. When we look at the three skill group levels for all workers (Figure 3.4b) we find some stable results over the whole period of investigation and some that vary with the sub-period. 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 3.4a) Tunisia witnessed an increase for unskilled and a decrease for medium skilled in both periods, although the magnitudes differ. This means that self-employed which share increased in the Tunisian labor force were mainly medium-skilled workers.

[2]Kthiri, Wajd, ”Inadéquation des qualificationsen Tunisie: quels sont les déterminants du sous-emploi?”, 2019.

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

Figure 3.4: Changes in employment shares by skill levels

(a) Paid employees (b) All workers



When we look at occupational at the 9 groups level (Table 3.2, illustrated in Figure A3.2) we find that clerical support workers were the biggest losers in terms of jobs with an acceleration after the revolution. This decline may be attributed to the routinization, since this group includes many high routine intensive jobs such as keyboard-operating clerks, numerial clerks, etc. Technicians and associate professionals whose share was slightly increasing in the first period were characterized by a significant decrease after 2010. On the opposite, skilled agricultural workers and services employees were the main beneficiaries in terms of employment creation. For category 5 (service workers) the number of protective workers almost doubled between 2010 and 2017 while it decreased slightly between 2000 and 2010 (table A3.1). This increase after the Revolution was due to the significant increase of security forces hiring (policemen, national guard, etc.). Shop salespersons increased also significantly as well as housekeepers and restaurant service workers.

As shown by figure 3.5 the sectoral distribution of 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% of GDP, there was a slight relaunch of agriculture after the revolution as this sector has probably been the least disrupted by social tensions. The movement of deindustrialization in favor of services continued between 2000 and 2015[4]. 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 favor of the three lowest occupation groups (Table 3.2). The group "technicians and associate professionals" was the only exception. Another interesting result is the decrease of 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 of the Autor et al.'s (2003) routinization hypothesis, at least in the pre-revolution period. From 2000 to 2017, the labor market in Tunisia witnessed a strong decrease of routine-manual tasks 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 3.2). The descriptive statistics, however, reveal also different patterns of the occupational evolu-

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

Table 3.2: Descriptive statistics by occupational groups at 1-digit level

	Level			Growth rate	
	2000	2010	2017	2000-10	2010-17
Panel A. Share of employment (%)					
1 Managers	3.53	3.40	4.55	-0.38	4.24
2 Professionals	10.62	11.08	10.79	0.43	-0.38
3 Technicians	6.70	6.91	5.37	0.32	-3.54
4 Clerks	9.80	7.52	5.39	-2.61	-4.65
5 Services	10.12	10.93	14.38	0.78	4.00
6 Skilled Agricultural	3.89	3.12	4.08	-2.19	3.90
7 Trades Workers	14.90	13.81	13.79	-0.75	-0.02
8 Machine Operators	15.28	15.99	14.45	0.46	-1.43
9 Elementary	25.16	27.23	27.20	0.79	-0.01
B. Mean weekly earnings (constant 2010 prices)					
1 Managers	193.43	203.34	164.60	0.50	-2.97
2 Professionals	162.55	175.29	181.66	0.76	0.51
3 Technicians	121.73	122.46	137.82	0.06	1.70
4 Clerks	102.08	101.58	109.58	-0.05	1.09
5 Services	83.96	80.33	91.83	-0.44	1.93
6 Skilled Agricultural	45.07	50.99	61.29	1.24	2.66
7 Trades Workers	69.80	81.19	91.53	1.52	1.73
8 Machine Operators	69.57	74.16	82.63	0.64	1.56
9 Elementary	51.26	59.15	75.32	1.44	3.51

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

tion, for example the decrease of the technical jobs, the contrasting employment-share changes of the agricultural group over the pre- and post-revolution periods, or the earnings degradation of the managers after the Revolution. These dynamics of the labour market resulted from the complex interplay between various factors, among them are the computerization of the routine jobs, structural transformation, the decline of the education premium and the 2011 Revolution. Therefore, it is not straightforward to claim the preeminent role of 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 the most routine-intensive, the decrease of their share leads to a U-shaped pattern of the employment evolution conditional on the initial level of wage. More precisely, the specification is as follows:

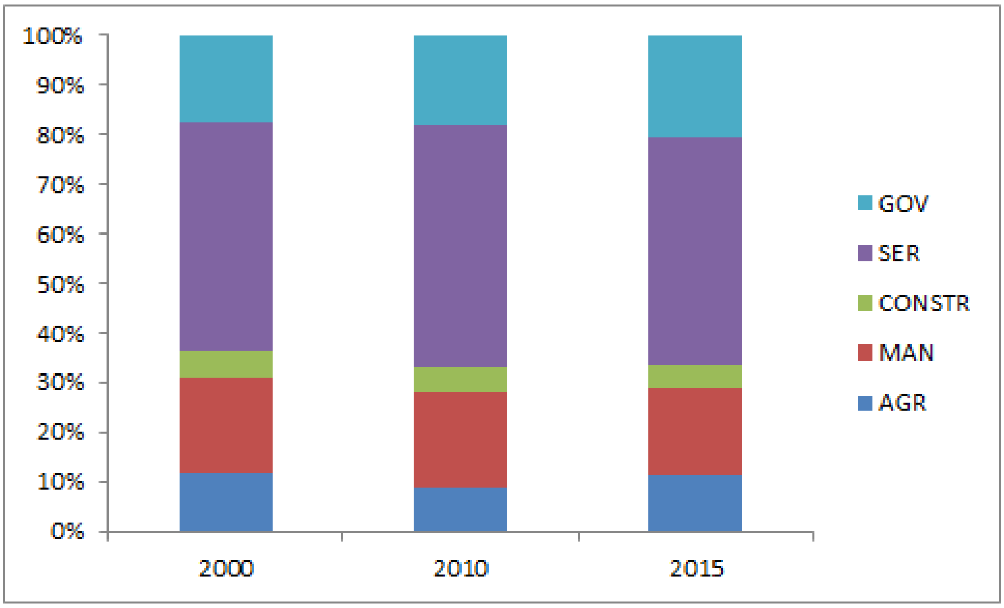
$$\Delta EmploymentShare_i = \beta_0 + \beta_1 Earnings_{i,t-1} + \beta_2 Earnings^2_{i,t-1} \tag{1}$$

Sebastian (2018) extended this specification to the relationship between wage growth and the initial level of wage:

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

Accordingly, 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. Although no significant evidence of the employment polarization is found in Tunisia, the regression of log earnings growth on lagged log earnings provides a support for the earnings polarization in both periods (Table 3.3). Despite the

Figure 3.5: Distribution of GDP by sector 2000-2015



significant regression estimates, the plot of the changes in log earnings over skill percentiles (figure 3.7b) shows an L-shape pattern with the increase of log earnings at the lower end of the distribution and the stagnancy of log earnings at the upper end of the distribution. Tunisia's asymmetric earnings polarization seems to have been mainly led by the increase of the lowest wages.

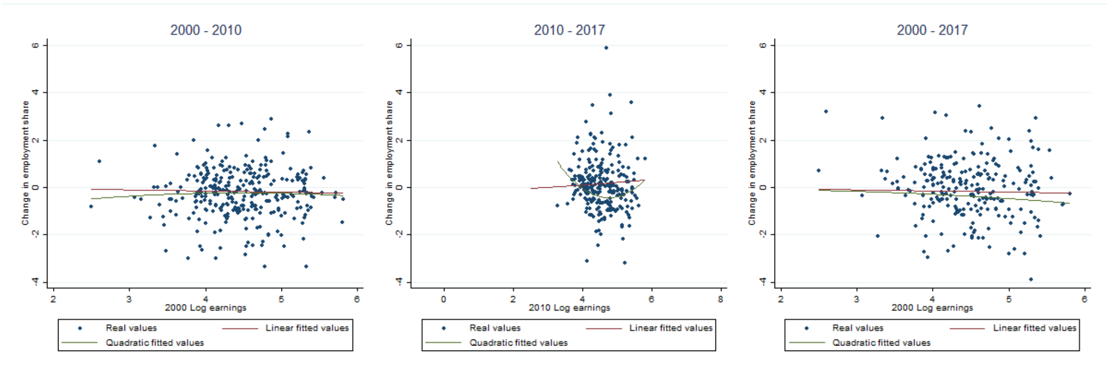
Table 3.3: Job and earnings polarisation tests

	Change in employment share			Change in log mean earning		
	2000-10	2010-17	2000-17	2000-10	2010-17	2000-17
Log mean earnings	1.443	-6.585	0.097	-1.969***	-1.372***	-2.253***
(t-1)	(0.890)	(4.132)	(1.742)	(0.321)	(0.439)	(0.298)
Sq. Log mean earnings	-0.176	0.693	-0.031	0.202***	0.128**	0.215***
(t-1)	(0.109)	(0.453)	(0.216)	(0.038)	(0.050)	(0.038)
Constant	-3.062*	15.205	-0.179	4.793***	3.631***	5.864***
	(1.805)	(9.251)	(3.417)	(0.668)	(0.965)	(0.581)
Observations	305	250	239	305	250	239
R-squared	0.015	0.074	0.009	0.499	0.372	0.688
Adj. R-squared	0.009	0.066	0.001	0.496	0.367	0.686
p-value of F-test	0.271	0.018	0.670	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 3.6: Fitted plots of job and earnings polarization

(a) Job



(b) Earnings

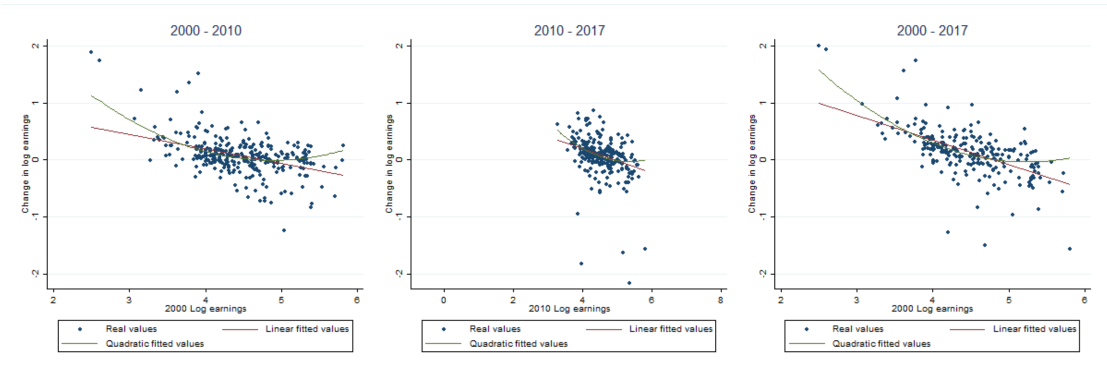
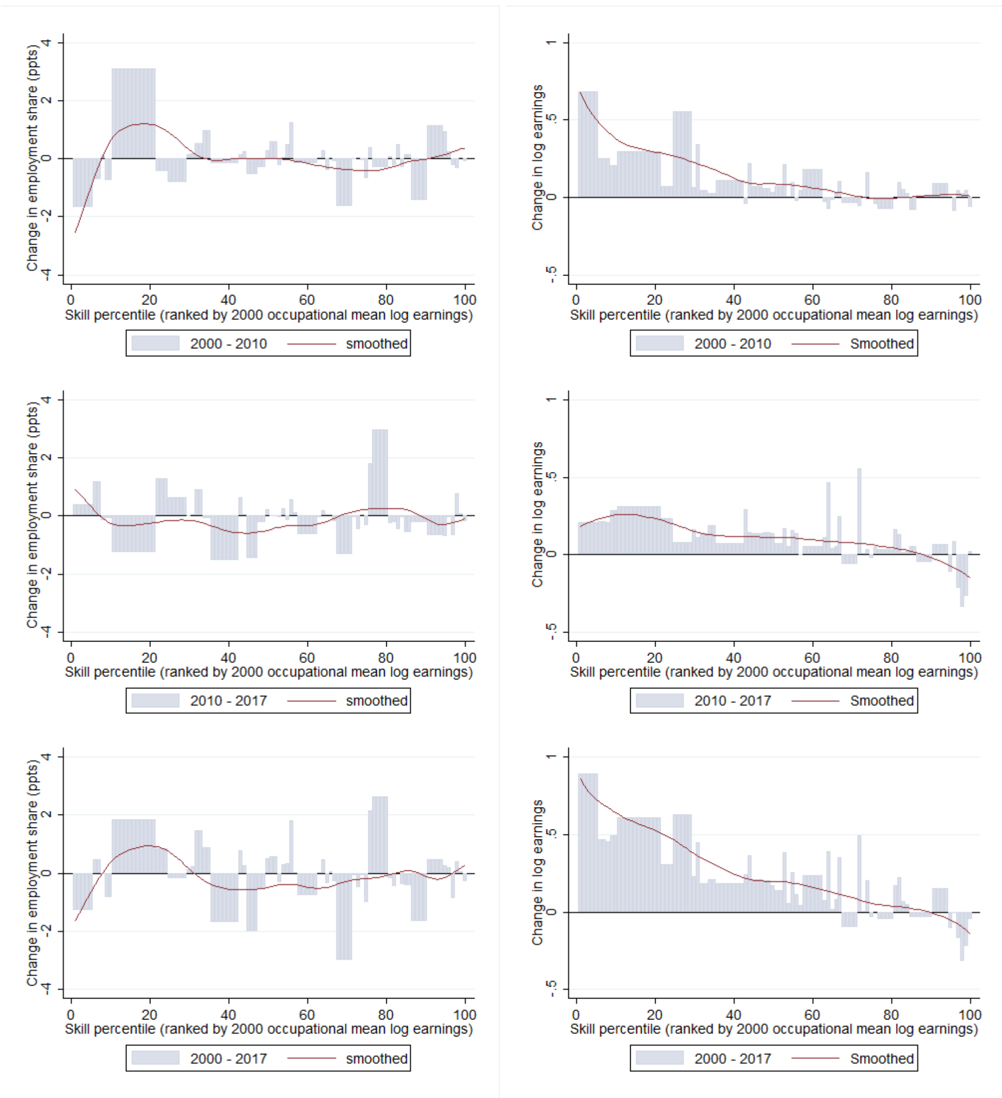


Figure 3.7: Change in log earnings and employment share by skill percentiles

(a) Employment share (b) Log earnings



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 the job polarization. In this section, we further investigate the explanatory power of the routinization hypothesis using the different measures of the task intensity of jobs. Our base specification uses the routine task intensity (RTI) constructed from O*NET data, following the approach of Autor et al. (2003), Firpo et al. (2011, 2018) and Autor et al. (2003, 2013). The use of O*NET, a US survey data, to construct the task content measures for developing countries is criticized due to large differences in technological progress, globalization, structural change and skill supply (Lewandowski et al., 2019). As a result, for robustness check, we use the country-specific RTI calculated by Lewandowski et al. (2020). Their regression-based method allows to include the country-specific factors that can contribute to the variance of RTI across countries. Table 4.4 shows that the country-specific RTI, measured at the 2-digit ISCO occupational level, increased between 2000 and 2010 and between 2010 and 2017, while the O*NET RTI increased only during the first period then declines. In both cases the RTI increased from 2000 to 2017.

Table 4.5 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 2000 occupational mean log earnings in Figure 4.8. The distributions of the two indices, despite their stability over time, were quite different. While the panel (a) shows an inverted U-shape curve, the panel (b) shows a monotonically declining curve of RTI over skill percentiles. In this case, the distribution of the O*NET RTI seem to be more in line with the routinization hypothesis: the middle income jobs have higher routine task intensity than the lowest income jobs.

Table 4.4: Average routine task intensity over years

	2000	2010	2017
O*NET RTI	0.535	0.609	0.567
Country-specific RTI	0.402	0.417	0.434

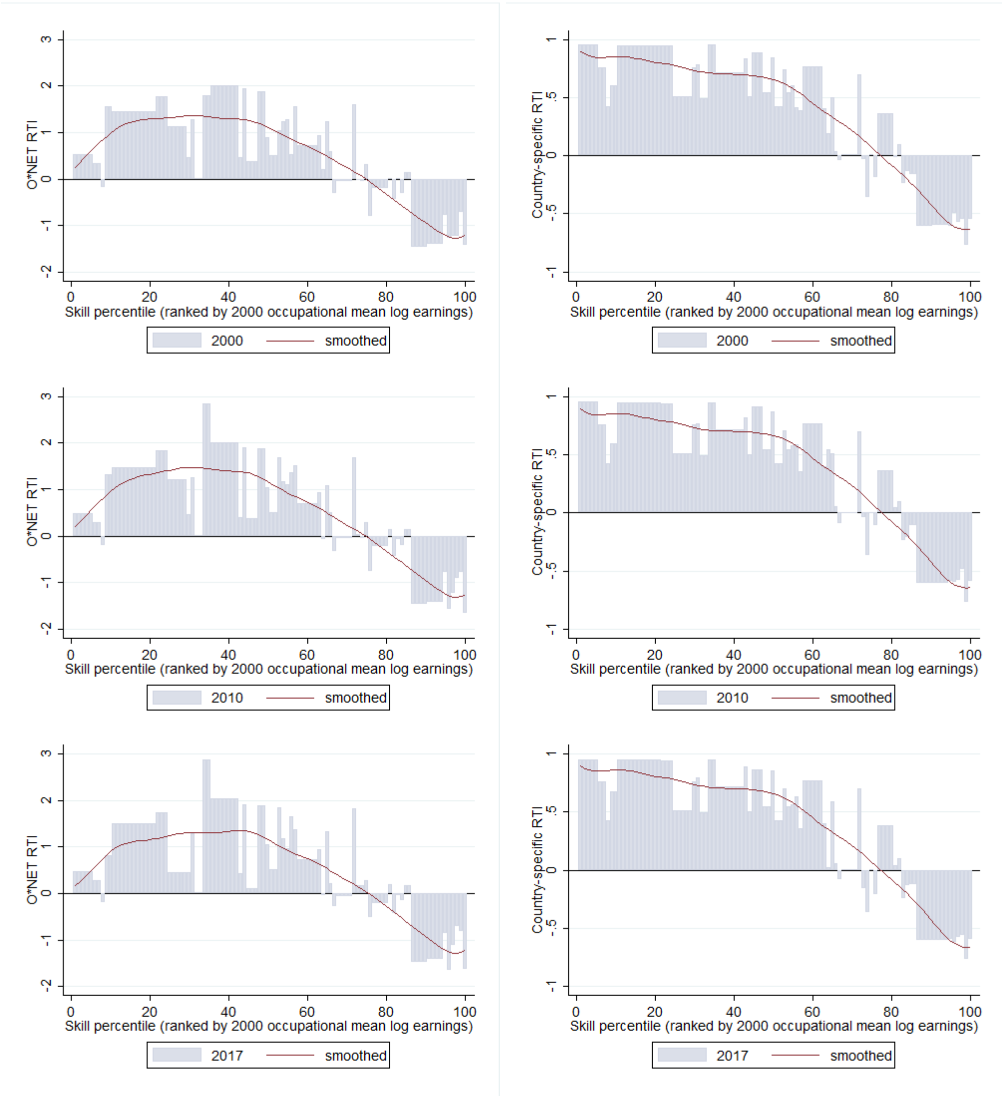
Table 4.5: Correlation between log earnings, O*NET RTI and Country-specific RTI

	Log earnings	O*NET RTI	Country-specific RTI
Log earnings	1.0000		
O*NET RTI	-0.4841	1.0000	
Country-specific RTI	-0.6672	0.7182	1.0000

In figure 4.9 and 4.10 we decompose the changes of the average RTI into the contributions of occupational groups and industries. The contributions of occupational groups to the changes in the average RTI did not, however, completely correspond to the fact observed in Table 3.2 that the shares of workers in the routine-occupational groups had declined. For example, the share of the clerical group dropped 4 percent from 2010 to 2017, but its contribution to the average RTI was still positive during this period. This seeming inconsistency requires us to look at the RTI composition of the occupational groups besides its employment shares. In the case of the clerical group, the share of routine jobs, such as data entry operators (4113), calculating-machine operators (4114), mail carriers and sorting clerks (4142) and coding and proof-reading clerks (4143), is

Figure 4.8: Routine task intensity over skill percentiles

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



relatively small in comparison to the jobs with negative RTI such as secretaries (4115) and production clerks (4132). Therefore, the decrease in these jobs drove up the average RTI of the clerical. We also witness an increase of the high routine-intensive jobs in the elementary group, such as mining, construction and manufacturing labourers (931 and 932), while lower routine-intensive jobs within the group, such as messengers, porters and doorkeepers (915) and agricultural labourers (921) reduced over the period from 2000 to 2017. From the industrial perspective, manufacturing, despite its decreasing employment share, has been the largest contributor to the increase of the average RTI, followed by the public administration sector. As the average RTI increased over time, other driving forces might have greater impacts on the employment distribution of the Tunisian labor market than the routinization. Our suggestion is that the public sector played an important role in maintaining the high routine-intensive jobs. This hypothesis will be further scrutinized in the following section.

In the next step, we apply the same specification as in the polarization tests to study the correlation between routine task intensity and the dynamics of employment and earnings in Tunisia. We use data at 3-digit occupational level for the O*NET RTI and

Figure 4.9: Decomposition of changes in average RTI by occupational group

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

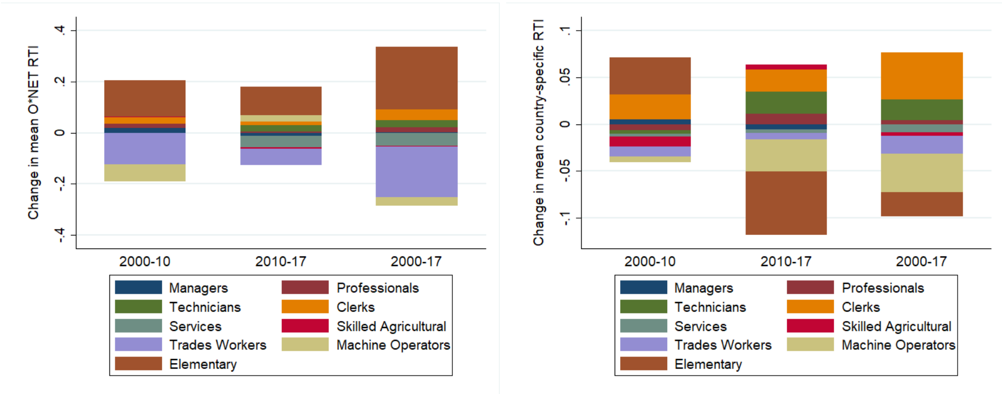
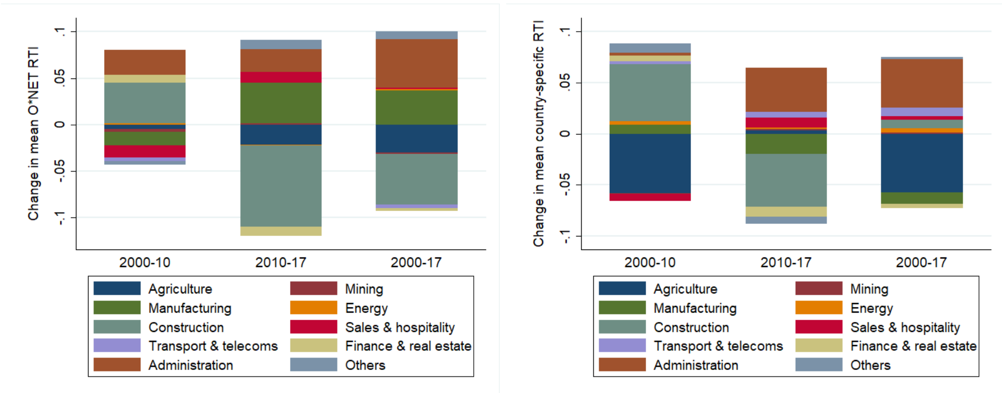


Figure 4.10: Decomposition of changes in average RTI by industry

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



data at 2-digit occupational level for the country-specific RTI. The models are as follows:

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

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

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

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

The regressions results for employment share change and log earnings change are presented in Table 4.6 and Table 4.7 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 routine-intensive 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 are similar. These results confirm the absence of job polarization and the L-shape evolution of earnings conditional on the initial earnings that we observed in 3.

In Figure 4.11 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 to visualize the positively linear relationship between earnings growth and RTI.

Table 4.6: OLS regression of change in employment share on the initial level of RTI

	Change in employment share					
	2000-10	2010-17	2000-17	2000-10	2010-17	2000-17
O*NET RTI	0.338	-0.183	0.156	0.261	-0.157	0.125
(t-1)	(0.277)	(0.140)	(0.261)	(0.314)	(0.159)	(0.303)
Sq. O*NET RTI				0.090	-0.026	0.037
(t-1)				(0.112)	(0.087)	(0.152)
Constant	-0.100	-0.207	-0.306	-0.198	-0.178	-0.347
	(0.253)	(0.202)	(0.327)	(0.263)	(0.265)	(0.413)
Observations	305	250	239	305	250	239
R-squared	0.084	0.040	0.012	0.094	0.042	0.014
Adj. R-squared	0.081	0.036	0.0083	0.089	0.034	0.005
p-value of F-test	0.224	0.191	0.550	0.274	0.420	0.802
Country-specific RTI	1.163	0.137	1.485	0.046	0.622	0.626
(t-1)	(1.081)	(0.420)	(0.936)	(0.271)	(0.463)	(0.636)
Sq. Country-specific RTI				2.886	-1.255	2.220
(t-1)				(2.160)	(1.364)	(2.480)
Constant	-0.249	-0.185	-0.503	-1.078	0.191	-1.140
	(0.430)	(0.290)	(0.675)	(0.698)	(0.650)	(1.208)
Observations	26	26	26	26	26	26
R-squared	0.113	0.005	0.146	0.254	0.084	0.213
Adj. R-squared	0.076	-0.037	0.111	0.189	0.004	0.145
p-value of F-test	0.293	0.747	0.126	0.423	0.420	0.146

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

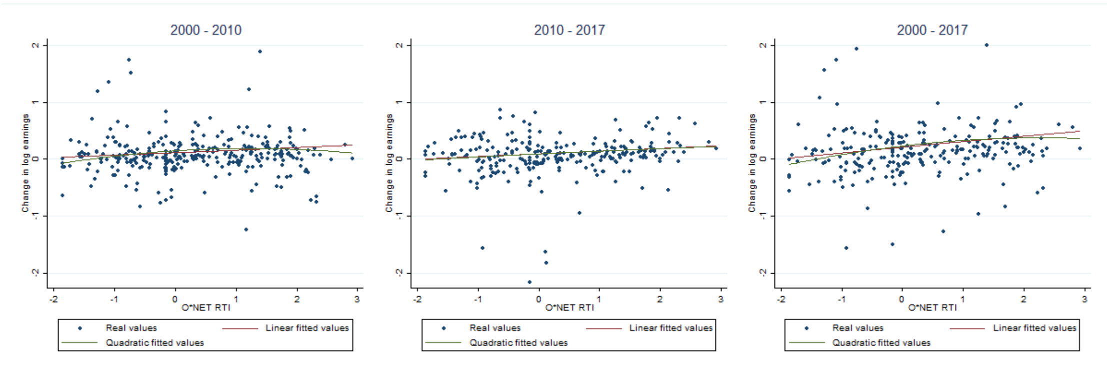
Table 4.7: OLS regression of change in log earnings on the initial level of routine task intensity

	Change in log earnings					
	2000-10	2010-17	2000-17	2000-10	2010-17	2000-17
O*NET RTI	0.044**	0.049***	0.102***	0.067***	0.051***	0.125***
(t-1)	(0.018)	(0.017)	(0.032)	(0.026)	(0.019)	(0.036)
Sq. O*NET RTI				-0.028	-0.003	-0.027
(t-1)				(0.019)	(0.008)	(0.026)
Constant	0.118***	0.090***	0.203***	0.148***	0.093***	0.233***
	(0.034)	(0.018)	(0.047)	(0.052)	(0.022)	(0.070)
Observations	305	250	239	305	250	239
R-squared	0.048	0.138	0.146	0.080	0.139	0.164
Adj. R-squared	0.0445	0.135	0.142	0.0734	0.132	0.157
p-value of F-test	0.017	0.005	0.002	0.029	0.019	0.002
Country-specific RTI	0.166**	0.166***	0.326***	0.081	0.136***	0.215***
(t-1)	(0.067)	(0.033)	(0.083)	(0.061)	(0.023)	(0.070)
Sq. Country-specific RTI				0.219	0.079	0.289
(t-1)				(0.165)	(0.052)	(0.170)
Constant	0.074*	0.046***	0.119**	0.012	0.023	0.036
	(0.037)	(0.015)	(0.046)	(0.063)	(0.017)	(0.064)
Observations	26	26	26	26	26	26
R-squared	0.234	0.707	0.493	0.316	0.738	0.571
Adj. R-squared	0.202	0.695	0.471	0.257	0.716	0.534
p-value of F-test	0.02	0.000	0.001	0.030	0.000	0.000

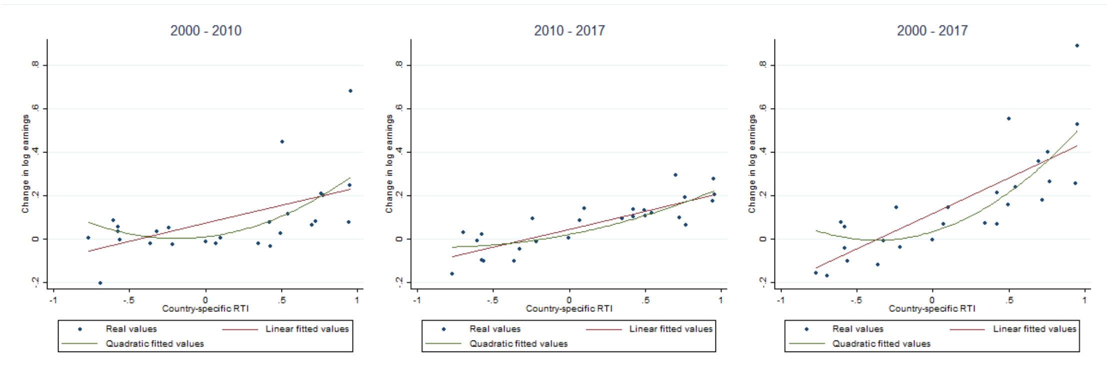
Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 4.11: Effect of RTI on occupational log mean earnings

(a) O*NET RTI - 4-digit occupations



(b) Country-specific RTI - 2-digit occupations



4.2 Shapley decomposition and RTI's contribution to the changes in 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 to decompose the non-additively decomposable inequality indices such as the Gini index into between-occupations and within-occupations contributions. As reported in Table 4.8 the differences between occupations, in other words, the specific characteristics of occupations, contributed around half of the overall inequality. It increased drastically before the Revolution from 49 percent to 55 percent, and dropped to 46 percent 7 years after. The main reason was probably the decrease of supply of workers for the most basic occupations and the increase of supply for the highest given the evolution of the educational structure of the workforce. Government policies and unions pressure may have contributed to accelerate this outcome.

The trend of the contribution is similar if we keep the employment share of the occupations unchanged over time. But if the occupational mean earnings is instead kept constant, the contribution of occupational characteristics to the total inequality would increase 2 percentage point in 2010 and 10 percentage point in 2017. That is to say 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 Gini concentration index. The RTI concentration index measures the extent to which the distribution of occupational average earnings deviates from the perfectly equal distribution. The difference is that occupations are ranked by their routine task intensity instead of the their average earnings. If the ranking of occupational groups by routine task intensity is similar to the ranking of occupational groups by average earnings, the RTI concentration index would be equal to the Gini index. In table 4.8, 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 routine task intensity) 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

As discussed in the previous sections, the changes in wage structure of the Tunisian labor market were driven by various forces, for instance, routinization, government policies (in the public sector), agreements with trade union which led to relatively uniform wage increases and service-led structural change (or deindustrialization). The evidences we found confirm that the difference in the routine nature of the job has not been the main driving force of the changes in earnings inequality in the Tunisian labor market over the last two decades. The remaining question is how much the other forces mentioned contributed to the changes in wage structure. To answer this question we firstly run a RIF regression of different inequality indices on the observed determinants, including occupation, industry, public sector, education and sex (coastal regions, youth and marital status are used as control variables). Results of the RIF regressions are presented in table A5.1 in the appendix. Then we decompose the changes in earnings

Table 4.8: 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	0.353	0.312	0.294	0.353	0.315	0.296	0.353	0.323	0.337
2. Between-occupations	0.175	0.171	0.134	0.175	0.171	0.135	0.175	0.185	0.187
% 2/1	49%	55%	46%	49%	54%	46%	49%	57%	56%
3. Within-occupations	0.178	0.141	0.160	0.178	0.143	0.160	0.178	0.138	0.150
% 3/1	51%	45%	54%	51%	46%	54%	51%	43%	45%
4. Gini between occupations	0.249	0.230	0.188	0.249	0.232	0.190	0.249	0.248	0.251
O*NET RTI									
5a. Concentration index (-RTI)	0.205	0.194	0.148	0.205	0.191	0.152	0.205	0.209	0.207
% 5a/4	82%	84%	79%	82%	82%	80%	82%	84%	83%
Country-specific RTI									
5b. Concentration index (-RTI)	0.236	0.215	0.168	0.236	0.216	0.172	0.236	0.235	0.238
% 5b/4	95%	93%	90%	95%	93%	90%	95%	95%	95%

inequality into wage structure and composition effects, as well as into the contribution of each determinant, using RIF decomposition (Firpo et al., 2011, 2018).

The results of the RIF decomposition are presented in table 5.9. Although most 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 explained about 11 percent of the observed reduction in the Gini coefficient in the first period. In the second period, on the contrary, the composition effect contributed to an increase in inequality, but this effect was very small and counteracted by the wage structure effect. The composition effect acted in opposite directions on the two halves of the distribution: it increased the 90-50 earnings gap while decreasing the 50-10 earnings gap. The disequalizing effect of the changes in characteristics was, however, totally offset by the changes in coefficients effect. Figure 5.12 plots the total change of real log earnings and its two components - wage structure and composition effects over earnings percentiles.

In terms of composition effects (illustrated in figure 5.14), the effects linked to education increased inequality at the top end (effect of 0.015 and 0.004 on the 90-50 gap), but decreased inequality at the bottom end (effect of -0.032 on the 50-10 gap). The public sector, as expected, contributed to the decrease of inequality in the 2000-2010 period: an effect of -0.012 on the 90-50 gap and an effect of -0.005 on the 50-10 gap. The composition effects associated with occupations also contributed to the reduction of the earnings inequality, but to a much lesser extent.

In terms of wage structure effects (visualized by figure 5.15), the results show that the covariates overexplained -0.637 of the -0.038 change in the 90-50 gap and -0.719 of the -0.119 change in the 50-10 gap from 2000 to 2010. From 2010 to 2017, the wage structure effects only contributed to the change in the 90-50 wage gap. Among the covariates, the public sector captured the best the changes in the coefficient effects which contributed -0.484 and -0.613 of the 0.038 and 0.119 decline in the 90-50 and 50-10 earnings gap. The equalizing effect of the public sector turned into the disequalizing effect in the 90-50 earnings gap in the second period, just like the composition effects. The set of covariates associated with education seems to go the wrong way in explaining the change in the 90-50 wage gap from 2000 to 2010. Indeed, the education premium might reduce the inequality at the bottom end but should increase inequality at the top end. However, as shown in table A5.1, education had an equalizing effect up to the secondary level, after its effect became disequalizing. The set of occupation covariates contributed 0.163 and 0.128 to the changes in the 90-50 gap in the first period and in the 50-10 wage gap in the second period. However these effects were absorbed by the covariates linked to the public sector during both periods, and the covariates linked to education in the second period.

The decomposition results relating to the occupation covariates bring us to the question related to whether the polarization exists within the private sector. To test this hypothesis, we remove the public sector and run a polarization test with the remaining data set. Interestingly, we find a job polarization after the Revolution and an earnings polarization before the revolution. The results of the polarization tests for the private sector are presented in table A5.2. This further confirms the counter-routinizing effect of employment and wage policies in the public sector in Tunisia.

Figure 5.12: RIF Decomposition of total earnings change into wage structure and composition effects

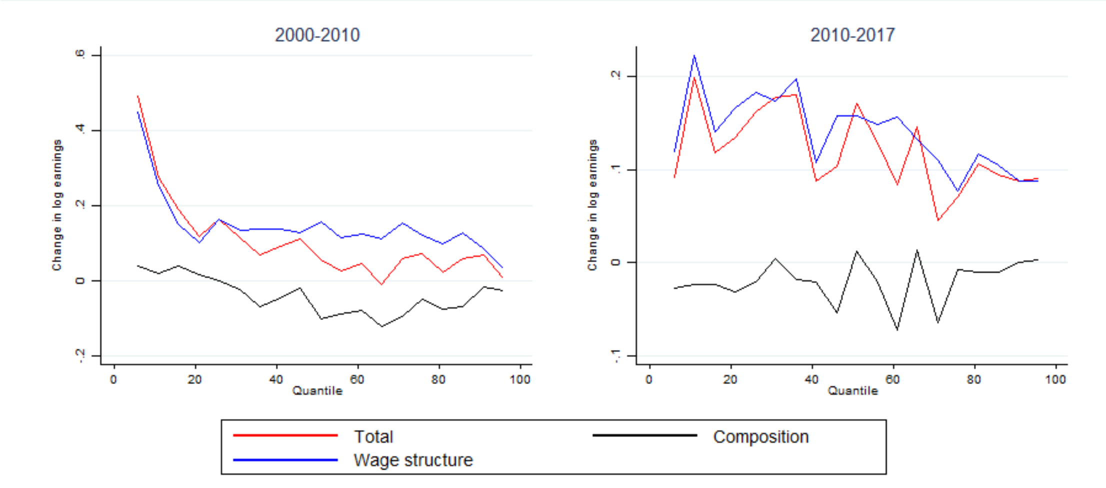


Figure 5.13: Detailed RIF decomposition of determinants of earnings changes - Total effect

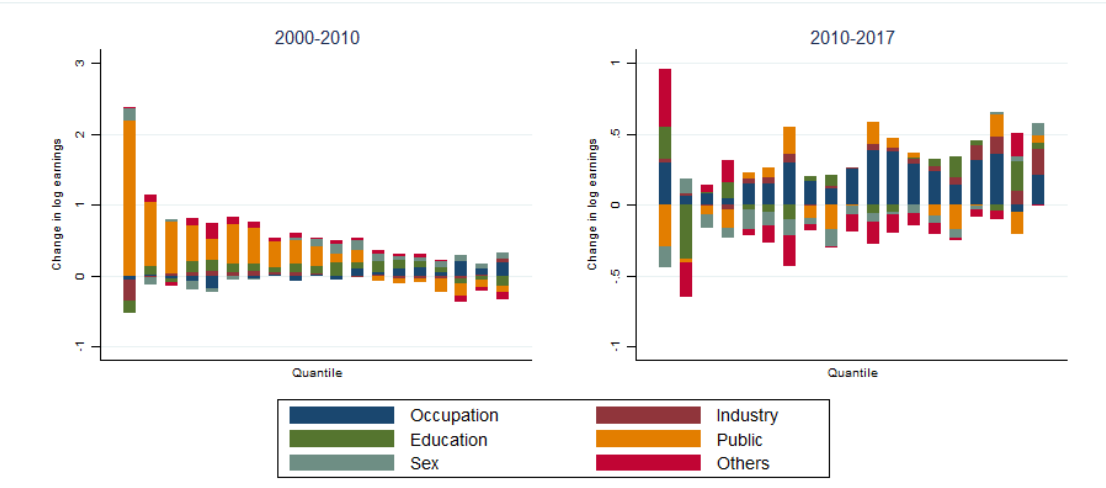


Figure 5.14: Detailed RIF decomposition of determinants of earnings changes - Composition effect

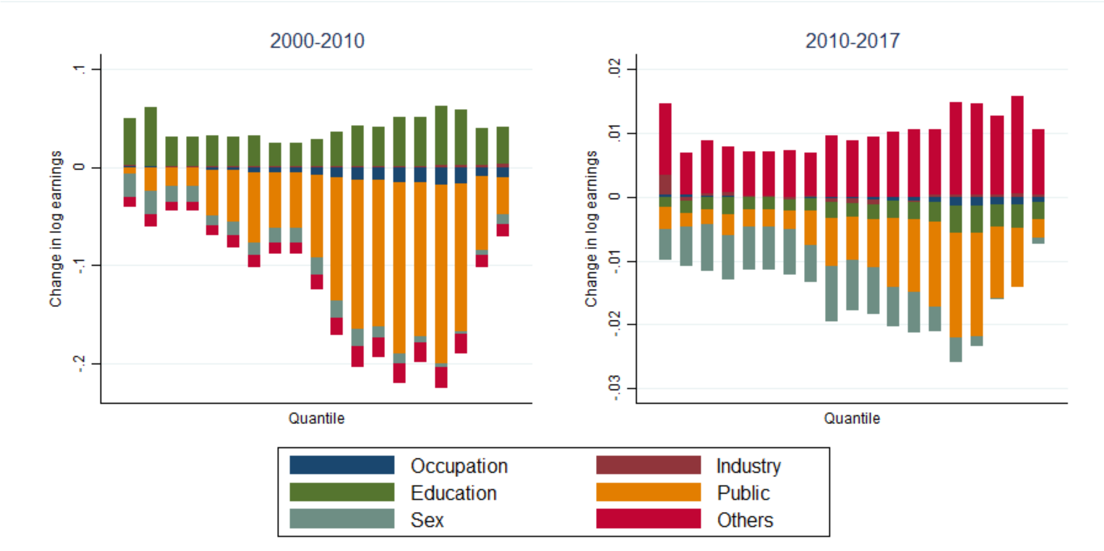


Figure 5.15: Detailed RIF decomposition of determinants of earnings changes - Wage structure effect

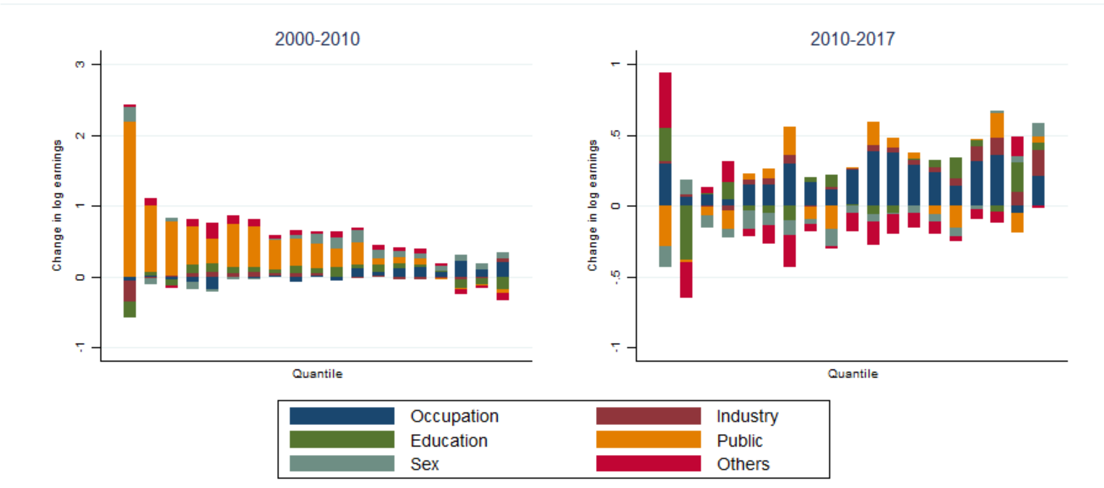


Table 5.9: RIF decomposition of changes in inequality indices

	Gini		Var		90-10		90-50		50-10	
	2000-10	2010-17	2000-10	2010-17	2000-10	2010-17	2000-10	2010-17	2000-10	2010-17
Total change	-0.045***	-0.028***	-0.270***	0.058***	-0.268***	-0.160***	0.002	-0.103***	-0.271***	-0.058***
Composition effects	-0.005**	0.002***	-0.026***	0.006**	-0.111***	0.035***	0.040***	0.081***	-0.151***	-0.046***
Wage structure effects	-0.039***	-0.030***	-0.244***	0.052***	-0.157***	-0.196***	-0.038***	-0.184***	-0.119***	-0.012
Composition effects										
Occupation	-0.002***	0.000	-0.005***	0.001	-0.009***	0.002	-0.004***	0.001	-0.006***	0.001
Industry	-0.001***	0.000	-0.002***	0.000	-0.001**	0.000	-0.005***	0.000	0.004***	-0.000
Education	0.001**	0.001***	-0.003*	0.004***	-0.017***	0.005***	0.015***	0.004***	-0.032***	0.001**
Public sector	-0.005***	0.000	-0.041***	0.000	-0.062***	0.000	-0.012***	-0.000	-0.050***	0.000
Man	0.002***	0.000	0.002***	-0.000	0.022***	0.000	0.008***	0.000	0.014***	-0.000
Youth	-0.000	-0.000***	0.000	0.001	0.000	0.001*	0.000**	0.001	-0.000	0.001
Coastal	0.001***	0.000***	0.004***	-0.004***	0.009***	0.003***	0.005***	0.003***	0.005***	-0.000
Married	0.001***	0.000	0.001**	-0.000	0.006***	0.002***	0.002***	0.001*	0.004***	0.001***
Specification error	-0.002	0.001**	0.018***	0.004*	-0.059*	0.021***	0.030***	0.072***	-0.089***	-0.051***
Wage structure effects										
Occupation	-0.004	0.006*	0.035	0.030	0.230***	0.111***	0.163***	-0.017	0.068	0.128***
Industry	-0.006	0.030***	0.151***	0.005	0.047	0.024	-0.062***	0.097***	0.109**	-0.073***
Education	-0.014	0.026***	-0.057	0.182***	-0.419***	0.408***	-0.172***	-0.026	-0.248***	0.434***
Public sector	-0.173***	0.019**	-0.882***	-0.050	-1.096***	0.093***	-0.484***	0.085***	-0.613***	0.008
Man	0.015**	0.023***	-0.009	-0.064**	0.241***	-0.140***	0.011	0.163***	0.229***	-0.303***
Youth	-0.021**	-0.007	-0.216***	0.076	-0.266***	0.058**	-0.027	0.013	-0.239***	0.045*
Coastal	0.007*	0.010***	0.090***	0.111***	-0.005	0.073***	-0.032***	0.003	0.027	0.070***
Married	-0.012***	0.009***	-0.053***	0.018	-0.089***	0.105***	-0.034**	0.032***	-0.055*	0.073***
Reweighting error	-0.001*	0.000***	-0.001	0.002***	-0.014***	0.003***	-0.007***	0.001**	-0.007**	0.002***

6 Conclusion

The objective of this paper was to investigate the links between inequality and the changing nature of jobs in a revolution context. It was also to study the determinants of inequality variation including the 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 labor. The employment and wage policies in the public sector since the Revolution also played a role in reducing inequality. Moreover, a wage polarization is highlighted, but unlike developed countries, Tunisian polarization seems to have been mainly led by the increase of the lowest wages similarly to what has been observed in China.

In terms of jobs, the share of tertiary educated in employment increased until 2010, but decreased after the Revolution, mainly for self-employed whose share increased in total employment. The main explanation lies in the increase of the share of agriculture and the share of unskilled Government workers under the revolutionary pressure.

Despite a significant reduction in clerical positions, the aggregate routine task index increases, which was probably due to public recruitment policy and to the increase of routine tasks within the manufacturing sector. When we remove the public sector we end up with a job polarization and a wage polarization only before the Revolution, which confirms the role of public policies in the Revolution era.

The Shapley decomposition showed that half of the earnings inequality resulted from the between-occupations differences most of which could be attributed to the RTI of jobs.

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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A Appendix

A.3 Changes in job distribution and earnings inequality

Figure A3.1: Adaptive kernel densities

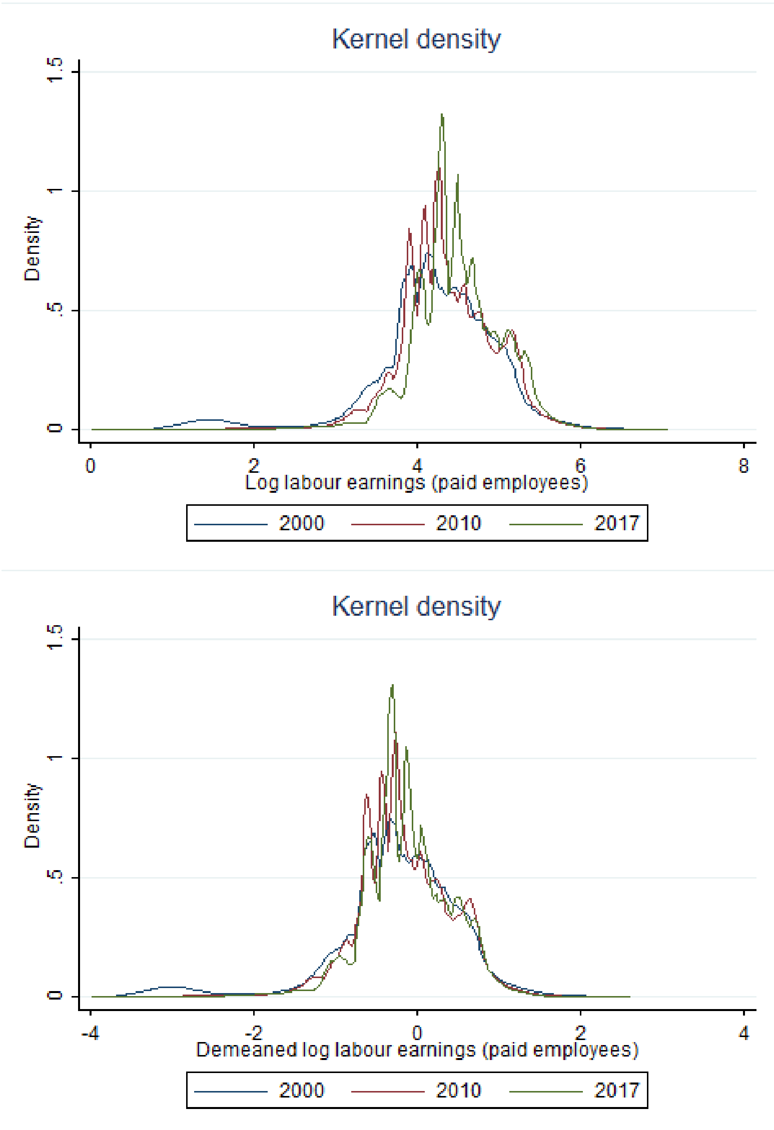
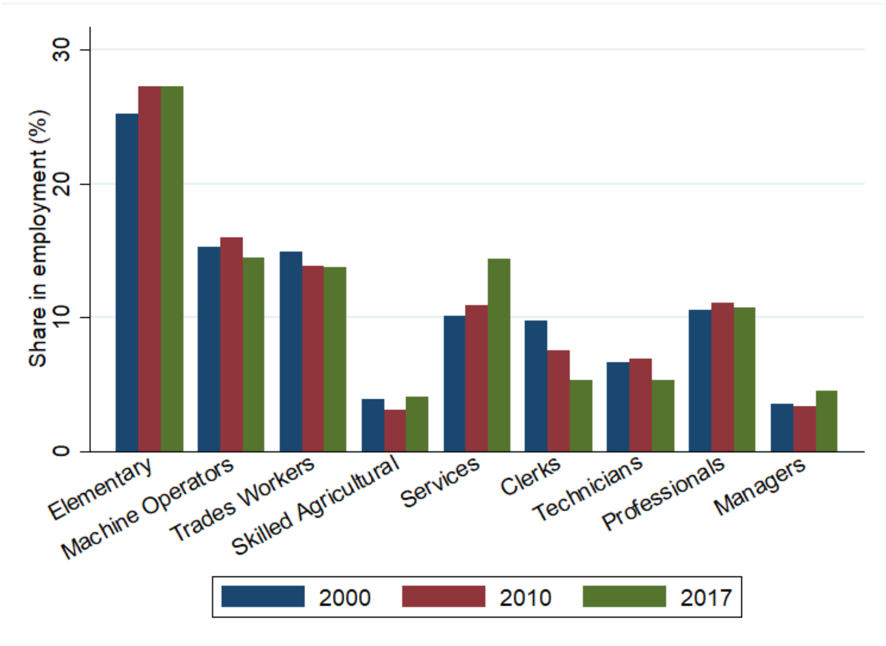


Figure A3.2: Employment shares by occupational groups at 1-digit level

(a) Paid employees



(b) All workers

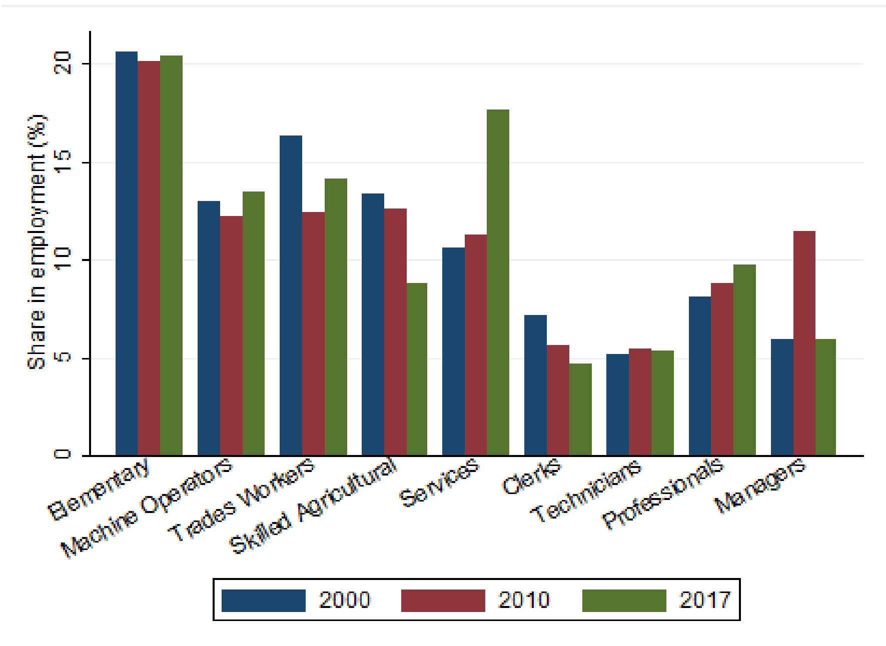
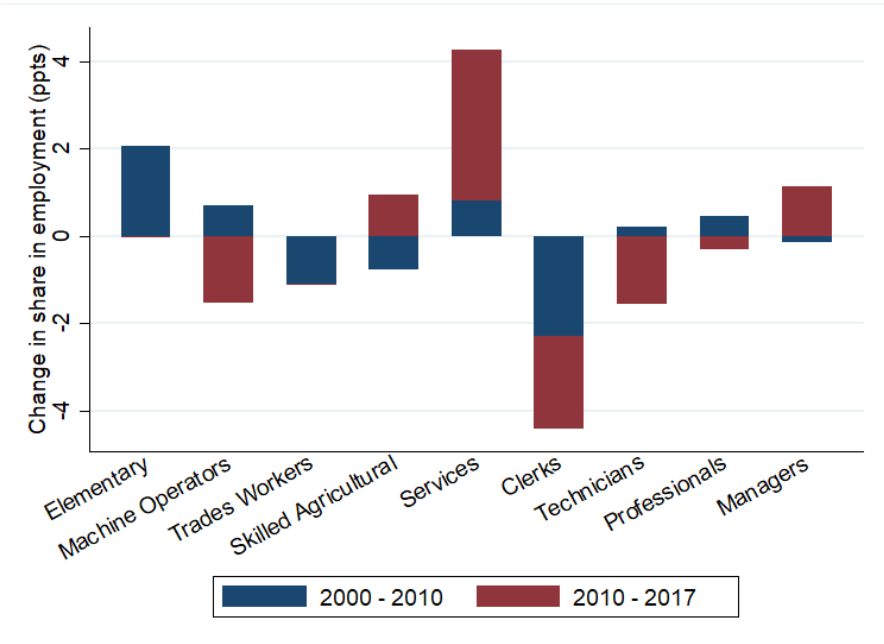


Figure A3.3: Changes in employment shares by occupational groups at 1-digit level

(a) Paid employees



(b) All workers

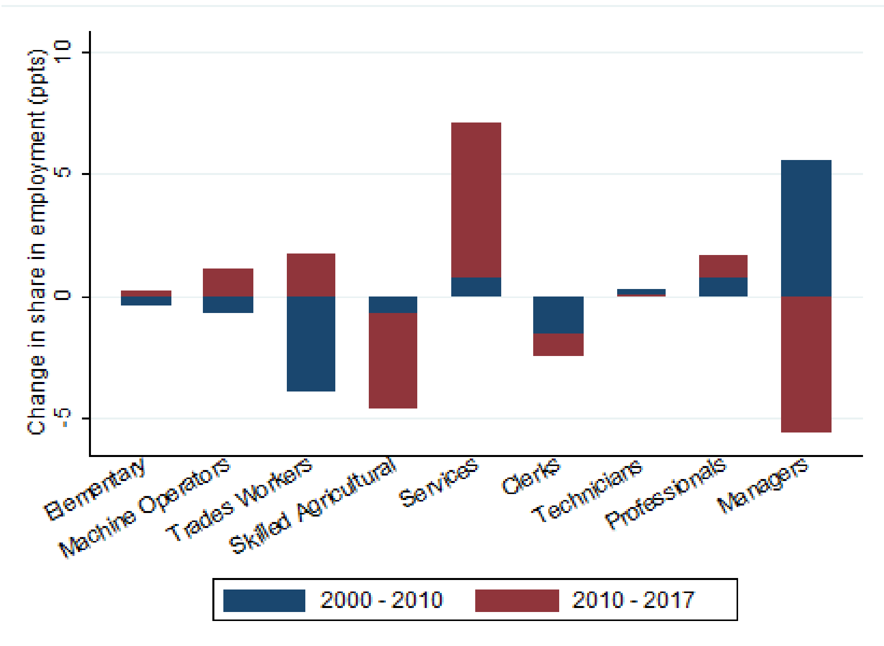
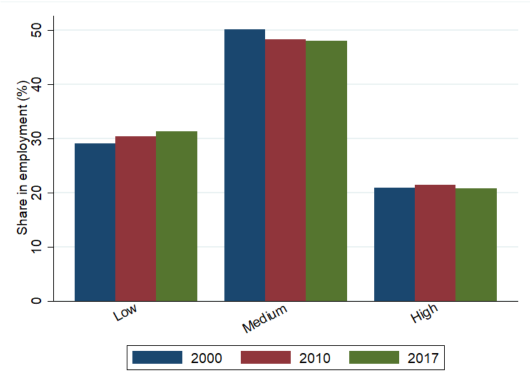


Figure A3.4: Employment shares by skill levels

(a) Paid employees



(b) All workers

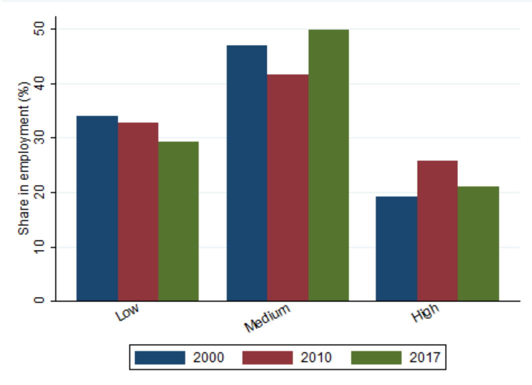
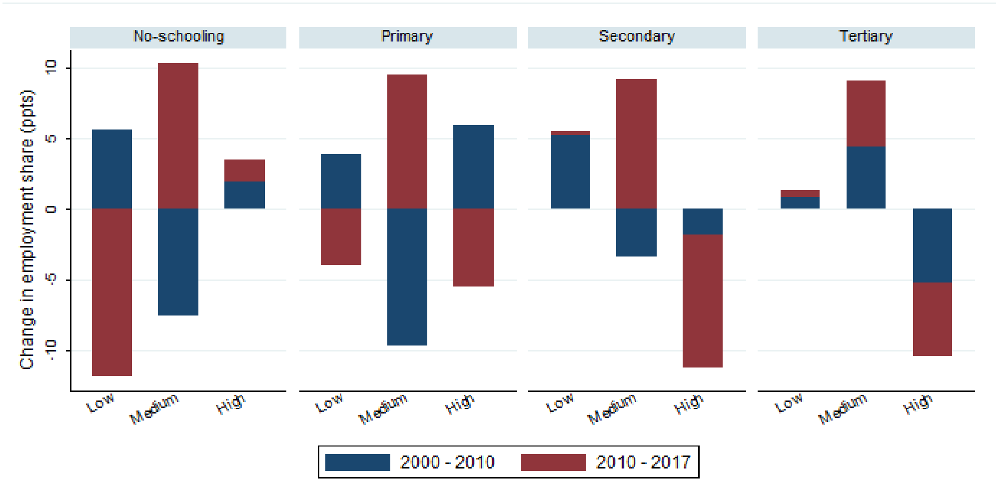


Figure A3.5: Changes in employment shares by education levels

(a) Paid employees



(b) All workers

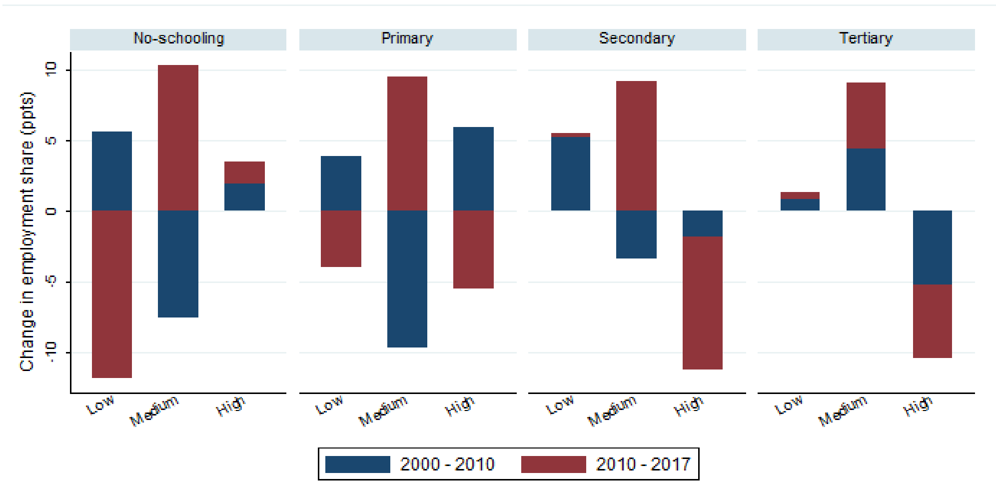


Figure A3.6: Employment shares by education levels: All workers

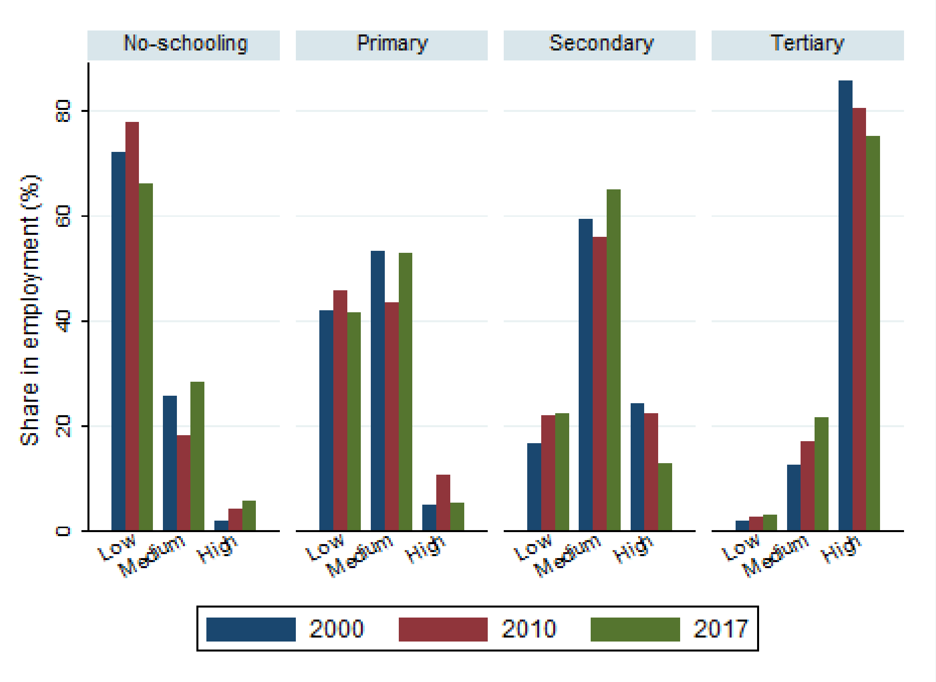


Figure A3.7: Smooth changes in employment share by occupational groups at 2 digit level

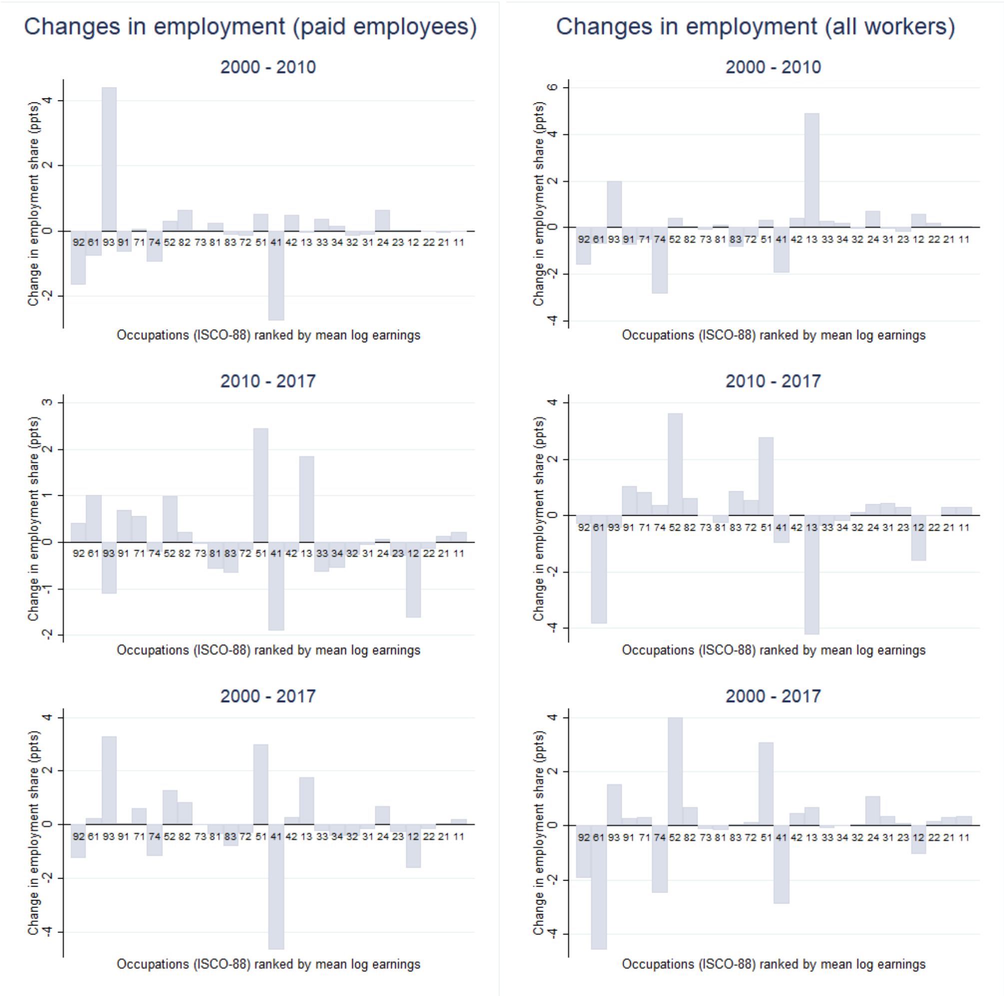


Figure A3.8: Employment distribution by education levels

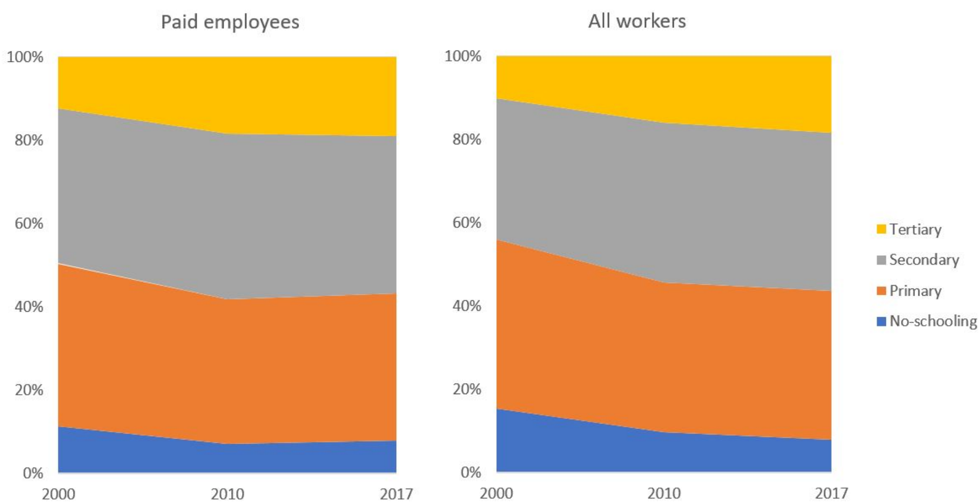


Figure A3.9: Changes in employment shares by skill quintiles

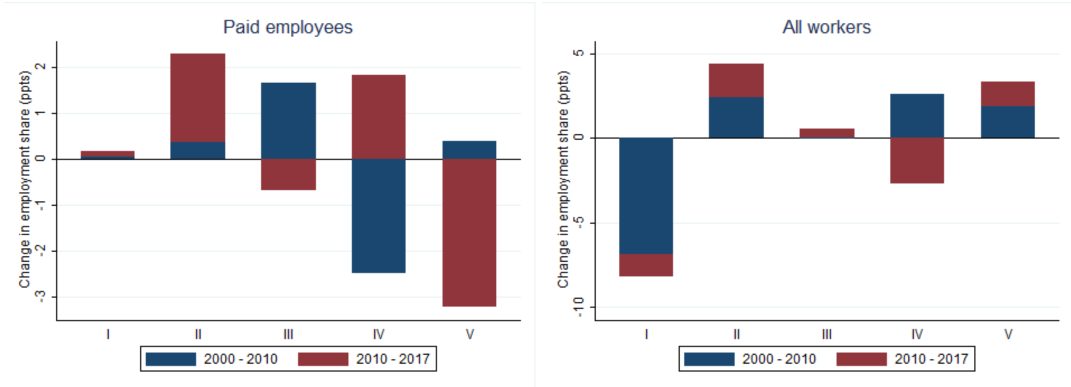


Figure A3.10: Changes in employment shares by skill quintiles and sectors

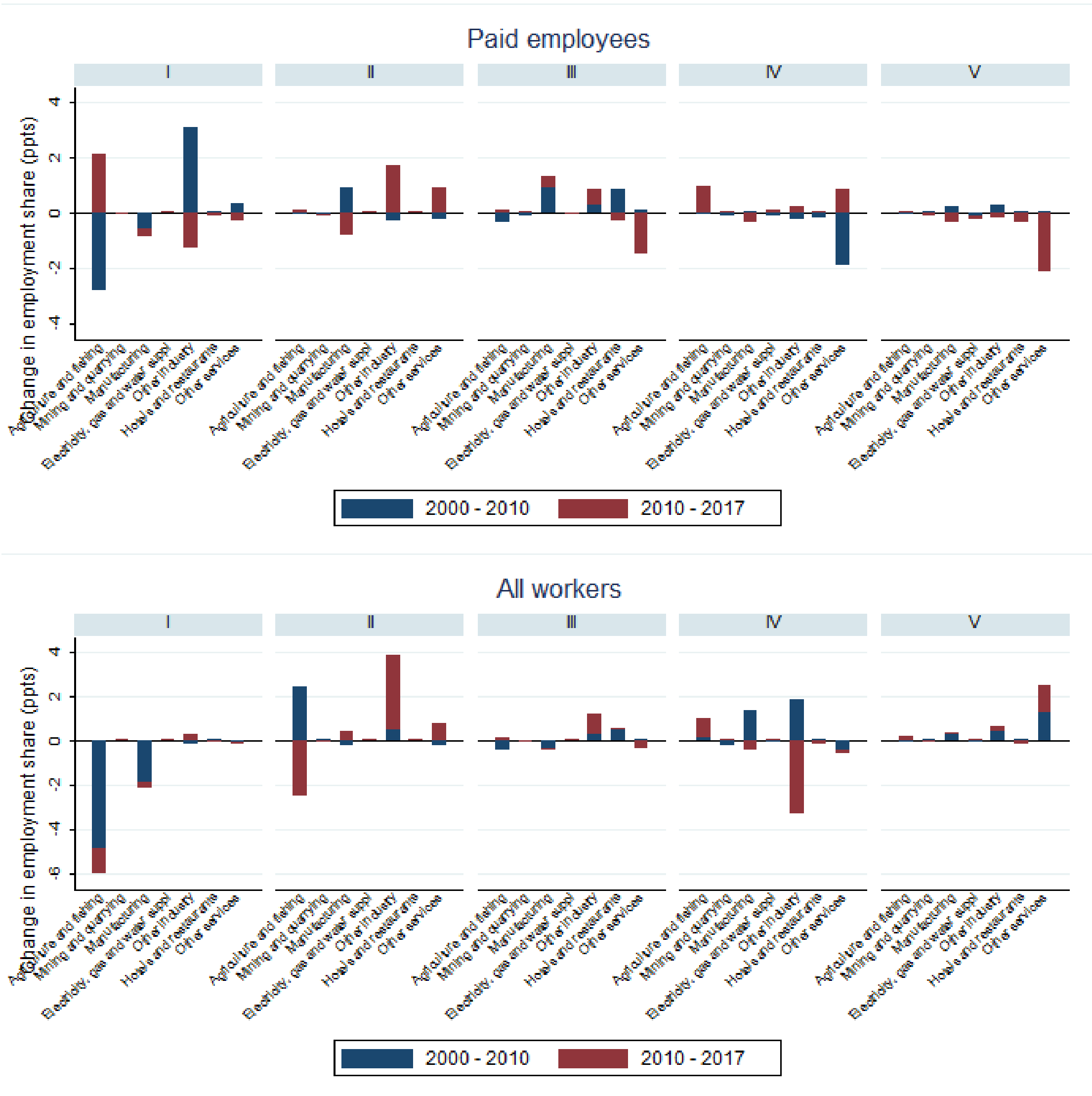


Table A3.1: Employment shares by occupation categories for ISCO88 categories 4 and 5

	2000	2010	2017
411 Secretaries and keyboard-operating clerks	4.891	3.236	1.904
412 Numerical clerks	1.166	0.503	0.168
413 Material-recording and transport clerks	1.676	1.615	0.755
414 Library, mail and related clerk	0.578	0.261	0.279
419 Other office clerks	0.159	0.101	0.690
421 Cashiers, tellers and related clerks	0.565	0.698	0.453
422 Client information clerks	0.756	1.095	1.129
511 Travel attendants and related workers	0.251	0.231	0.151
512 Housekeeping and restaurant services workers	2.618	3.203	3.182
513 Personal care and related workers	0.217	0.364	0.216
514 Other personal services workers	0.604	0.704	0.558
516 Protective services workers	3.642	3.345	6.191
521 Fashion and other models		0.002	
522 Shop salespersons and demonstrators	2.310	2.839	3.756
523 Stall and market salespersons	0.464	0.225	0.303

A.4 Task-based analysis

Figure A4.1: Task content by measures

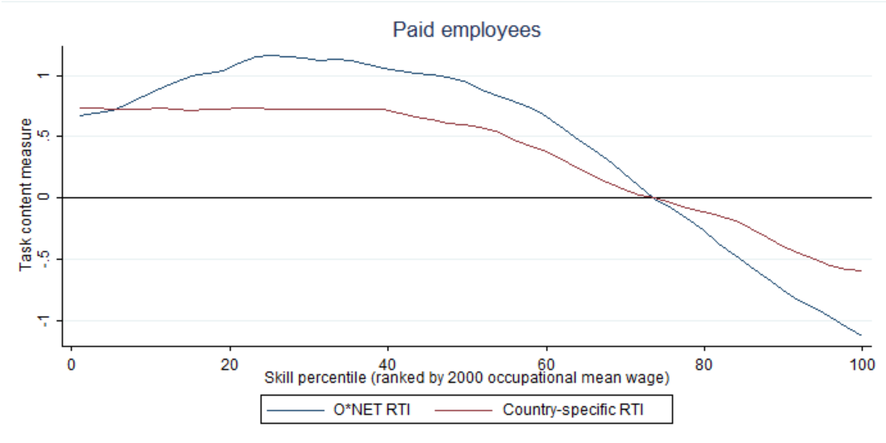


Figure A4.2: O*NET RTI Task content by components

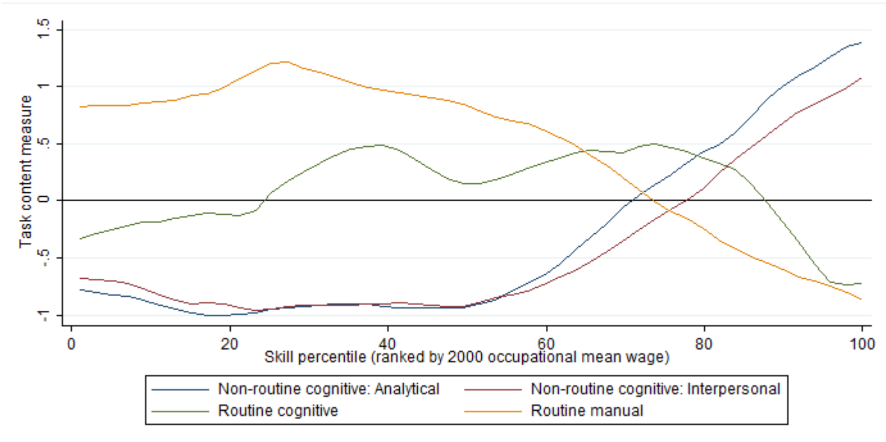


Figure A4.3: Change in log earnings and employment share of occupations ranked by O*NET RTI (Paid employees)

(a) Employment share

(b) Log earnings

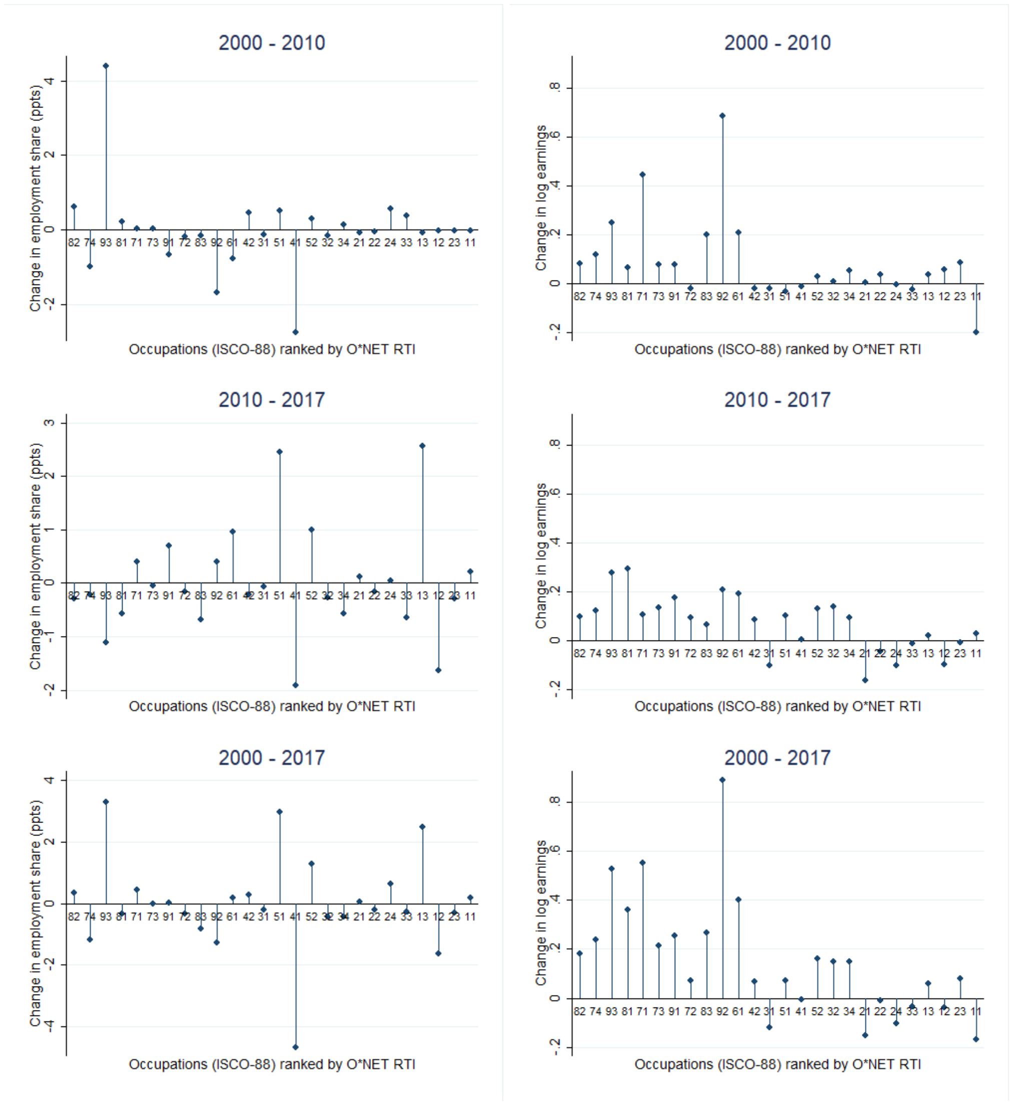


Figure A4.4: Change in log earnings and employment share of occupations ranked by Country-specific RTI (Paid employees)

(a) Employment share

(b) Log earnings

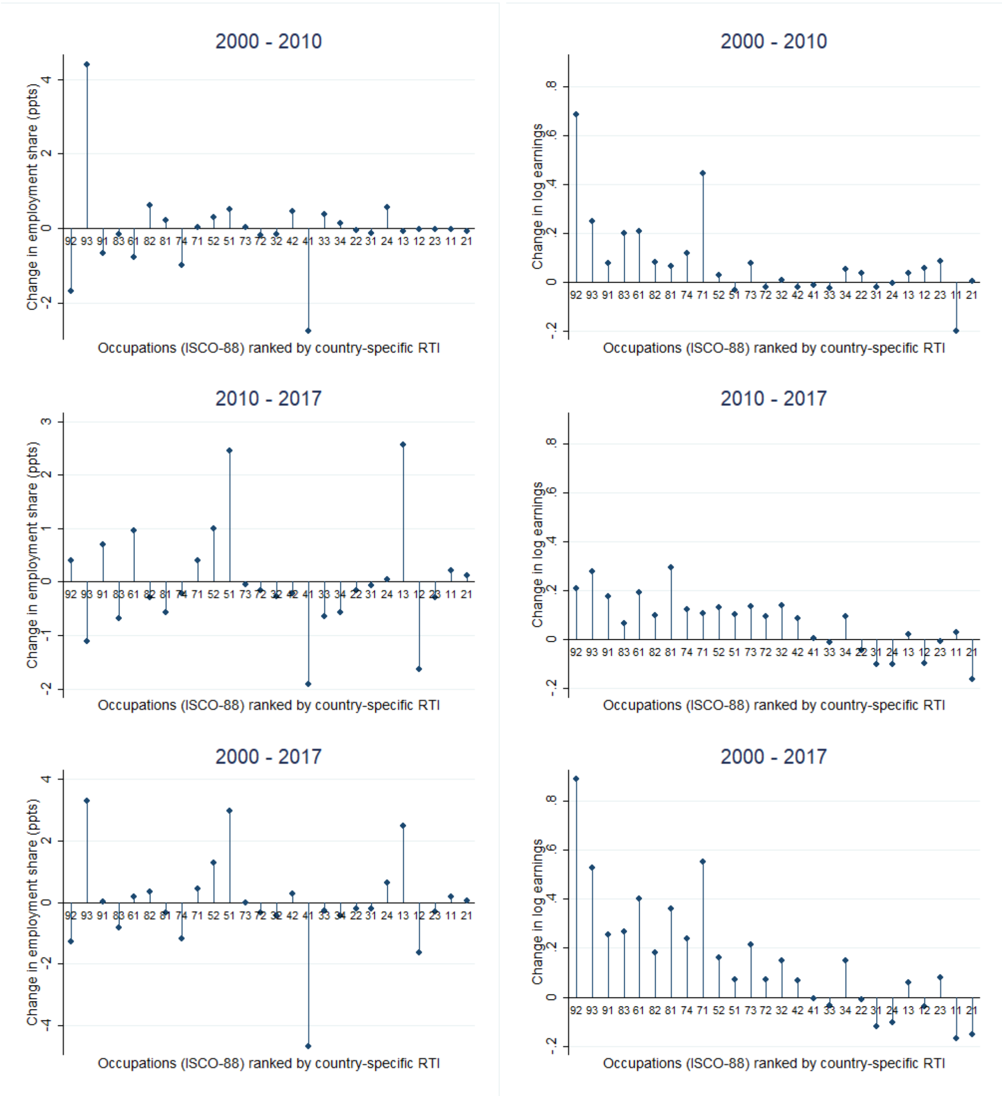


Figure A4.5: Changes in employment share by occupational groups at 2 digit level, ranked by RTI (All workers)

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

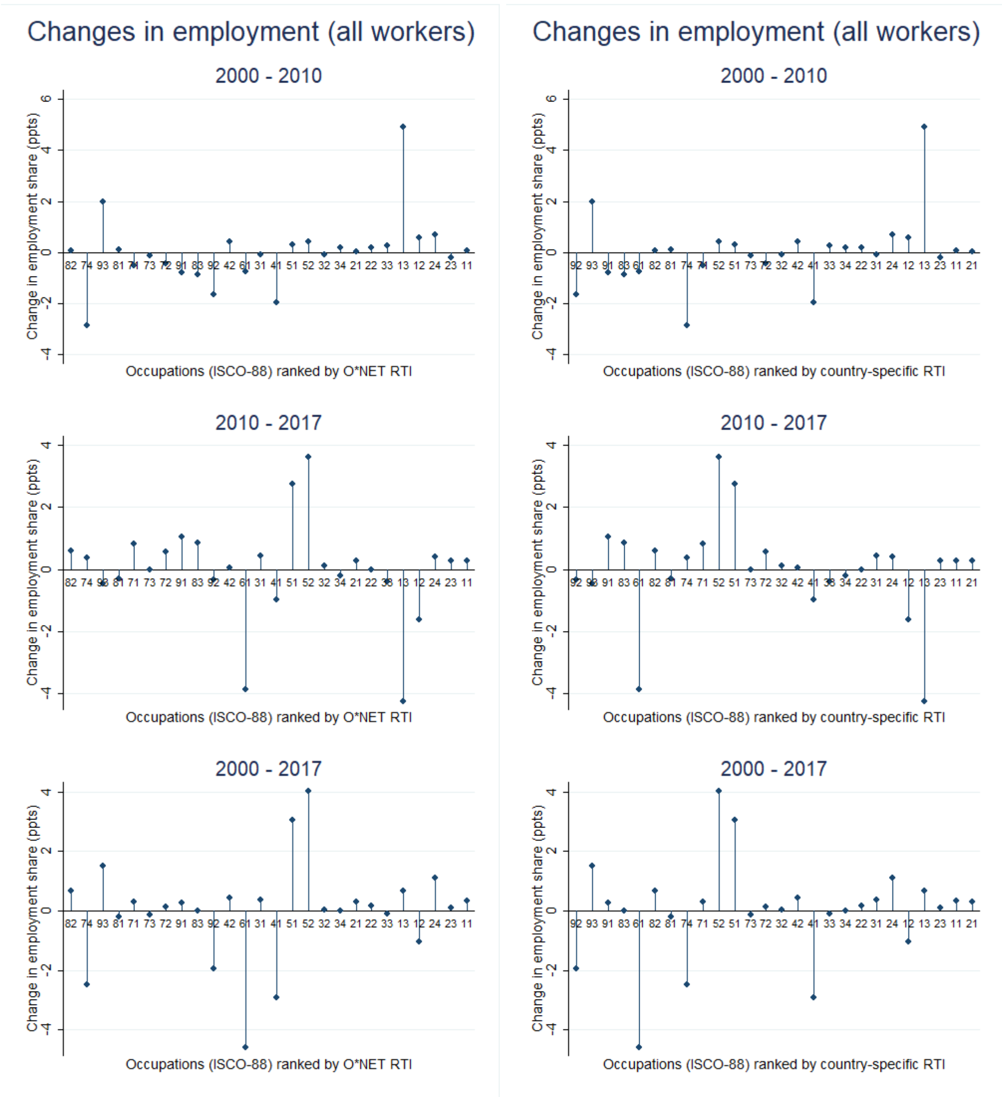


Figure A4.6: Concentration curves - 2010

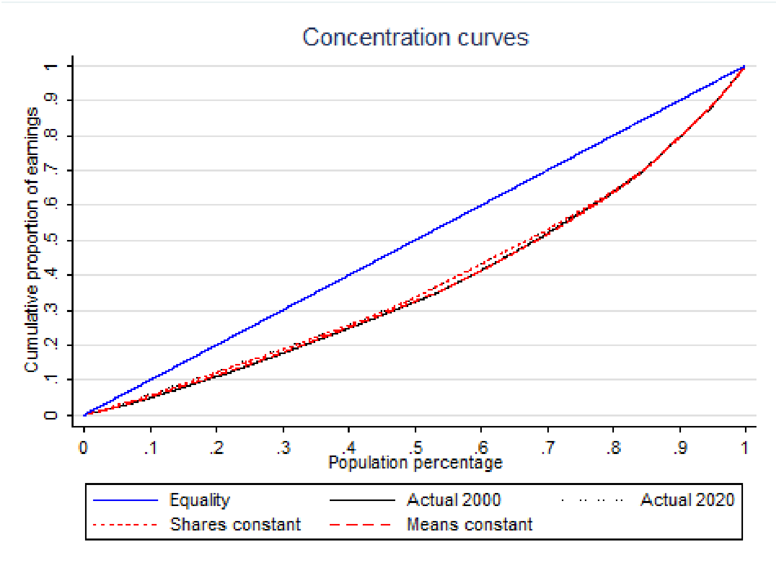
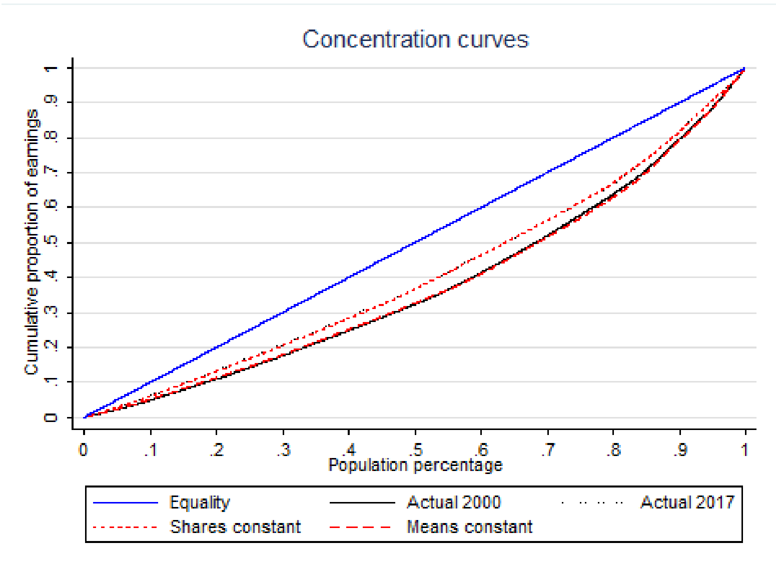


Figure A4.7: Concentration curves - 2017



A.5 Determinants of changes in earnings inequality

Table A5.1: RIF regressions of determinants of inequality

	Gini			Var		
	2000	2010	2017	2000	2010	2017
Occupation (Ref: 1 Managers)						
2 Professionals	-0.132***	-0.155***	-0.016	-0.225***	-0.306***	-0.177
	(0.029)	(0.015)	(0.018)	(0.059)	(0.058)	(0.136)
3 Technicians	-0.286***	-0.398***	-0.189***	-0.608***	-0.790***	-0.547***
	(0.028)	(0.013)	(0.020)	(0.055)	(0.056)	(0.129)
4 Clerks	-0.326***	-0.434***	-0.248***	-0.742***	-0.851***	-0.669***
	(0.025)	(0.013)	(0.014)	(0.053)	(0.062)	(0.124)
5 Services	-0.292***	-0.366***	-0.187***	-0.718***	-0.675***	-0.473***
	(0.024)	(0.012)	(0.013)	(0.057)	(0.062)	(0.119)
6 Skilled Agricultural	-0.326***	-0.366***	-0.150***	-1.829***	-0.775***	-0.496***
	(0.027)	(0.014)	(0.013)	(0.114)	(0.066)	(0.114)
7 Trades Workers	-0.284***	-0.383***	-0.189***	-0.602***	-0.707***	-0.523***
	(0.025)	(0.013)	(0.013)	(0.061)	(0.062)	(0.115)
8 Machine Operators	-0.311***	-0.431***	-0.238***	-0.813***	-0.917***	-0.685***
	(0.025)	(0.013)	(0.013)	(0.058)	(0.061)	(0.113)
9 Elementary	-0.234***	-0.344***	-0.196***	-0.678***	-0.813***	-0.644***
	(0.025)	(0.013)	(0.013)	(0.059)	(0.059)	(0.110)
Industry (Ref: 2 Agriculture)						
2 Mining	0.003	0.063***	0.051**	-1.044***	0.125*	0.330*
	(0.048)	(0.021)	(0.024)	(0.134)	(0.064)	(0.184)
3 Manufacturing	-0.117***	-0.099***	-0.037***	-1.417***	-0.227***	-0.009
	(0.013)	(0.006)	(0.006)	(0.093)	(0.022)	(0.057)
4 Energy	-0.131***	-0.057***	0.105**	-1.269***	0.269*	0.699***
	(0.021)	(0.013)	(0.049)	(0.111)	(0.163)	(0.217)
5 Construction	-0.173***	-0.139***	-0.089***	-1.431***	-0.318***	-0.133***
	(0.010)	(0.005)	(0.004)	(0.096)	(0.019)	(0.047)
6 Sales	-0.117***	-0.098***	-0.026***	-1.431***	-0.259***	-0.009
	(0.015)	(0.007)	(0.006)	(0.098)	(0.025)	(0.071)
7 Hospitality	-0.189***	-0.157***	-0.066***	-1.451***	-0.373***	-0.272***
	(0.015)	(0.007)	(0.006)	(0.101)	(0.034)	(0.067)
8 Transport & Telecom	-0.109***	-0.068***	0.009	-1.143***	-0.090**	0.241***
	(0.015)	(0.008)	(0.008)	(0.102)	(0.036)	(0.092)
9 Finance	-0.042	0.063***	0.271***	-1.089***	0.088	1.313***
	(0.034)	(0.022)	(0.037)	(0.104)	(0.083)	(0.357)
10 Real estate	-0.118***	-0.125***	-0.047***	-1.478***	-0.244***	-0.014
	(0.022)	(0.009)	(0.010)	(0.100)	(0.037)	(0.104)
11 Administration	-0.133***	-0.142***	-0.001	-1.292***	-0.181***	0.179**
	(0.014)	(0.008)	(0.008)	(0.092)	(0.036)	(0.075)
12 Education	-0.276***	-0.223***	-0.042***	-1.572***	-0.437***	-0.210***
	(0.019)	(0.010)	(0.011)	(0.096)	(0.037)	(0.081)
13 Health	-0.181***	-0.133***	-0.039***	-1.446***	-0.280***	-0.179***
	(0.019)	(0.009)	(0.009)	(0.101)	(0.035)	(0.063)
14 Other services	-0.070**	-0.048***	0.057*	-1.205***	-0.145***	-0.032
	(0.028)	(0.010)	(0.032)	(0.118)	(0.031)	(0.074)
15 Private households	-0.086***	-0.037***	0.003	-1.240***	-0.037	-0.016
	(0.017)	(0.007)	(0.009)	(0.152)	(0.028)	(0.068)

	Gini			Var		
	2000	2010	2017	2000	2010	2017
16 ONG	0.355	-0.088	0.398	-0.423	-0.256**	0.210
	(0.295)	(0.083)	(0.322)	(0.409)	(0.106)	(0.366)
Education (Ref: No schooling)						
Primary	-0.032***	-0.029***	-0.030***	-0.057	-0.077***	-0.096***
	(0.008)	(0.002)	(0.003)	(0.054)	(0.017)	(0.037)
Secondary	-0.058***	-0.039***	-0.032***	-0.119**	-0.071***	-0.030
	(0.009)	(0.003)	(0.004)	(0.056)	(0.020)	(0.041)
Tertiary	0.107***	0.036***	0.041***	0.231***	0.036	0.177***
	(0.016)	(0.004)	(0.007)	(0.062)	(0.031)	(0.061)
Public sector	0.100***	-0.013**	0.023***	0.430***	-0.075***	-0.118**
	(0.007)	(0.006)	(0.008)	(0.033)	(0.024)	(0.055)
Male	0.031***	0.030***	0.032***	0.077***	0.050***	-0.054*
	(0.006)	(0.002)	(0.004)	(0.024)	(0.012)	(0.030)
Youth	-0.018***	-0.007***	-0.011***	0.001	-0.009	0.016
	(0.005)	(0.002)	(0.003)	(0.030)	(0.014)	(0.037)
Coastal region	-0.042***	-0.027***	-0.007***	-0.209***	-0.098***	0.133***
	(0.005)	(0.002)	(0.002)	(0.026)	(0.011)	(0.024)
Married	-0.000	-0.016***	-0.001	-0.004	-0.017	-0.001
	(0.005)	(0.002)	(0.003)	(0.027)	(0.014)	(0.036)
Constant	0.645***	0.815***	0.456***	2.040***	1.549***	1.214***
	(0.033)	(0.017)	(0.020)	(0.135)	(0.086)	(0.182)
Observations	19,620	92,583	60,172	19,620	92,583	60,172
R-squared	0.158	0.221	0.205	0.111	0.036	0.020
Adj. R-squared	0.157	0.221	0.204	0.110	0.0354	0.0191
p-value of F-test	0.000	0.000	0.000	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table A5.2: Job and earnings polarisation tests - Private sector

	Change in employment share			Change in log mean earning		
	2000-10	2010-17	2000-17	2000-10	2010-17	2000-17
Log mean earnings	0.761	-7.666*	-2.823	-1.494***	0.212	-1.021*
(t-1)	(1.138)	(4.396)	(3.007)	(0.490)	(0.784)	(0.605)
Sq. Log mean earnings	0.005	0.796*	0.448	0.142**	-0.064	0.053
(t-1)	(0.161)	(0.471)	(0.375)	(0.064)	(0.094)	(0.084)
Constant	-3.311*	17.817*	3.616	3.935***	0.371	3.594***
	(1.979)	(10.047)	(5.718)	(0.927)	(1.626)	(1.059)
Observations	173	227	141	173	227	141
R-squared	0.159	0.103	0.020	0.461	0.347	0.682
Adj. R-squared	0.149	0.095	0.006	0.455	0.341	0.677
p-value of F-test	0.000	0.150	0.021	0.000	0.000	0.000

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1