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Implications of the changing nature of work for employment and inequality in Ghana

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Abstract: In this paper, we analyse the role of the changing nature of occupational employment and wages in explaining the trend in earnings inequality in Ghana between 2006 and 2017, a period in which there was a substantial transformation of the economy, with workers moving out of agriculture and generally taking more-skilled and less-routine jobs in services, in a context of a stagnant manufacturing sector and an oil-based expansion. We show that there was an initial decline in earnings inequality which is best explained by the fall in the skill premium that followed the expansion of education. This period was followed by a substantial increase in earnings inequality in which the skill premium continued to fall at a slower pace and there was a pro-rich change in the earnings returns to routine tasks performed by workers.

Key words: skills, tasks, occupational employment and wages, earnings inequality, Ghana

JEL classification: J21, J24, D63

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Note: The online Methodological and Technical Appendices are available here.

On 19 April 2022, Figure 9b was replaced, as the previous version incorrectly showed Figure 9a twice.

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1 Introduction

Technological advances and economic integration are transforming the organization of work and employment prospects around the world in new and different ways that we do not yet fully understand. Historically, new technologies have typically favoured skilled over unskilled labour by increasing its relative productivity and, therefore, its relative demand. Economists traditionally used this skill-biased technological change (SBTC) hypothesis to explain widening gaps in earnings between workers by skill levels (for an overview see, inter alia, Katz and Autor 1999; Katz and Murphy 1992), as observed in several countries at different stages of development.

However, this cannot explain why in many industrialized countries employment and earnings have declined in middle-skilled occupations over the past two decades, while increasing among both low- and high-skilled occupations. To explain this polarizing trend, labour economists have recently challenged the SBTC hypothesis, arguing that technological change does not necessarily depress the demand for all low-skilled workers, but rather that it does so for workers performing routine tasks that are easiest to replace by automation or that can be offshored to economies with lower wages. One of the main messages emerging from this literature is that 'tasks' are not synonymous with 'skills'. 'While there may be some overlap, non-routine or more interactive tasks […] are not necessarily identical with higher educational attainment' (Baumgarten et al. 2013: 132). In fact, recent research has shown that routine-task content tends to be highest in middle-skilled occupations. In consequence, this new strand of literature, which puts occupations at the forefront of the inequality debate, considers not skill-biased but routine-biased technological change and offshoring as the main factors driving job and wage polarization in the United States and Western Europe (see, inter alia, Acemoglu and Autor 2011; Autor et al. 2003; Baumgarten et al. 2013; Fernández-Macías and Hurley 2017; Firpo et al. 2011; Spitz-Oener 2006).

While the changing nature of work has been at the centre of recent analyses of the distribution of earnings in high-income countries, research on the patterns and trends observed in low- and middle-income countries remains scarce. This paper aims to fill this knowledge gap by providing an in-depth examination of the employment and inequality trends in Ghana since the mid-2000s, using data from the Ghana Living Standards Survey (GLSS) collected in 2005/06, 2012/13, and 2016/17. Our analysis focuses on shifts in the structure of employment and in the distribution of earnings within and across occupations that can be linked to changes in the supply and demand of skills, on the one hand, and to changes in the demand for and remuneration of routine versus non-routine tasks performed within specific occupations, on the other.

Because information on the specific task content of different occupations is only recently becoming available for a larger set of countries, most existing studies use data provided by the US Occupational Information Network (O*NET) to analyse task demand in countries around the world. This research, however, assumes that the task content of each occupation is identical across countries. Importantly, given persistent differences in the sectoral composition of employment, labour productivity, technology adoption, trade integration, and skills supply, jobs may utilize different skills and involve different tasks in Ghana compared with the US (Arias et al. 2014; Du and Park 2018; Hardy et al. 2018b; Lewandowski et al. 2019; Lo Bello et al. 2019). To address this notion, the principal measures of routine-task intensity (RTI) used in our analysis are derived from data provided by the Ghana Skills Toward Employment and Productivity (STEP) Survey, which we merge with the GLSS survey data at the occupational level. For comparative purposes, we also assess the patterns observed when task measures are constructed from O*NET.

We detect substantial structural changes in the composition of employment from 2005/06 to 2016/17, characterized mainly by a pronounced move of employment out of agriculture, which was most pronounced in the first subperiod up to 2012/13. As in many other Sub-Saharan African countries, this shift has been accompanied not by a rise in manufacturing employment but by an expansion of the service sector. These changes in the occupational structure imply a shift towards jobs demanding higher skills and involving less-routine tasks, resulting in a fall in the average RTI, regardless of the measure used. While earnings inequality among non-farm workers has not changed much over the full study period, striking differences are observed by subperiod: we find a decline in inequality during the first subperiod (2005/06–2012/13), in which the economy grew much faster, with largest earnings growth at the bottom percentiles and the smallest growth at the top; and a rise in inequality during the second subperiod (2012/13–2016/17), in which the economy kept growing but at a slower pace and with a clear 'pro-rich' pattern. In both periods, the trends in inequality are primarily explained by changes in the earnings structure, while the composition effect is small. Specifically, the decline in inequality in the first subperiod can be associated with a substantial decline in the education premium, following improvements in the level of education across workers, while the rise in inequality in the second subperiod is explained by a combination of two effects: a smaller equalizing effect due to a slow-down in the decline of the education premium was coupled with a disequalizing effect due to changes in the remuneration of non-routine jobs, relative to more-routine occupations.

The remainder of the paper is organized as follows. Section 2 provides a brief description of the data and decomposition approaches used in this paper. Section 3 presents a broad descriptive overview of the trends in employment and inequality in Ghana over the study period. The results of the decomposition exercises are reported in Section 4. Section 5 summarizes and concludes.

2 Data and methodology

2.1 Data sources and definitions

The main source of data for this study is the GLSS, a nationwide living standard survey conducted by the Ghana Statistical Service (GSS) (GSS 2008, 2014, 2018a). As a multi-purpose household survey, the GLSS collects detailed information on people's living conditions along various dimensions, including individual demographic characteristics, education, employment, and labour incomes. Seven rounds of data have been collected since 1987/88, which have served as an important tool in monitoring progress on poverty reduction strategies in the country.

In this study, we focus on the three most recent rounds of the GLSS, conducted in 2005/06 (GLSS 5), 2012/13 (GLSS 6), and 2016/17 (GLSS 7). We concentrate on these three waves mainly because the approach used in this study requires a detailed coding of occupations that can be mapped to data capturing the task content of occupations. The 2005/06 round was the first to use ISCO-88 classifications of occupations at the three-digit level, while earlier rounds used ISCO-68 at the two-digit level. As ISCO-88 resulted in the splitting of a significant number of ISCO-68 unit groups, a recoding of ISCO-88 (three digits) to ISCO-68 (two digits) would only be feasible at the expense of an important loss of information. The 2012/13 and 2016/17 rounds use ISCO-08 classifications of occupations at the four-digit level, which can be mapped to ISCO-88 unit groups at the three-digit level using correspondence tables provided by the International Labour Organization (ILO 2016). For occupations that have no unique match, we use the employment distribution from the 2005/06 wave to map the four-digit-level ISCO-08 occupations to the dominant three-digit-level ISCO-88 category (see online Technical Appendix for detailed mapping). The focus on the three latest rounds of GLSS is also made easier by the fact that the questionnaires are relatively similar, allowing for comparisons over time (GSS 2018b).

We restrict the sample to individuals of working age (15 to 64 years old) who did any work for pay, profit, or family gain in the last seven days at the time the survey was conducted. Individuals are classified into occupation groups according to the main economic activity that they spend most of their time on. As we are interested in studying the link between changes in the nature of work at the occupational level and inequality dynamics, for most of the analysis we limit the sample to those groups of workers for whom reliable earnings information is available in all three rounds. For paid employees, earnings are reported based on a one-shot question that asks about the amount (including bonuses, commissions, allowances, or tips) received for this work in a self-chosen time interval. From this information, weekly earnings are computed based on the number of hours worked in the reported period. In 2005/06 and 2012/13 this question was also administered to self-employed workers, but in 2016/17 it was not. Therefore, we impute missing earnings information by computing weekly business profits for self-employed workers operating non-farm household enterprises based on the respective survey module.[1] We exclude domestic employees, contributing family workers, and self-employed workers in agriculture from the analysis, because for these groups no reliable and inter-temporally comparable earnings information could be derived. To check the robustness of some of our findings, we split the sample by workers' formality status. Paid employees are defined as formal if they report having a written contract. Non-farm self-employed workers are defined as formal if their enterprise is registered with any government agency.

For comparative purposes, the task content of occupations is measured using two alternative data sources. First, as is standard in the literature, we match the ISCO-88 (three-digit) classifications in the GLSS survey data with task measures derived from O*NET (2003), collected from job incumbents and occupation experts for the US economy. Because information on the specific task content of occupations is only recently becoming available for a larger set of countries, most existing studies use the US O*NET task data to analyse task demand in countries around the world (see, for example, Arias et al. 2014; Du and Park 2018; Hardy et al. 2018b). This approach, however, assumes that the task content of occupations is identical across countries. Especially for low- and middle-income countries—like Ghana—this assumption may be problematic (Lewandowski et al. 2019).

Given large differences in labour productivity, technology adoption, and skills supply, recent research has shown that specific occupations utilize different skill sets and assign different tasks in low-, middle-, and high-income countries (Lewandowski et al. 2019; Lo Bello et al. 2019). In addition, with international trade and investment, poorer countries tend to specialize in routine tasks and richer countries in non-routine tasks (Grossman and Rossi-Hansberg 2008). To address this issue, we follow the approach suggested by Hardy et al. (2016) to construct country-specific task measures for Ghana, using information on the task content of occupations from STEP data collected in 2013 by the World Bank in collaboration with local partner institutions.[2]

[1] Due to this change in data collection, we observe an increase in the share of missing earnings information among non-farm self-employed workers especially in the last survey wave (no information from one-shot question available). A reweighting approach is used to correct for this.

[2] STEP is an initiative of the World Bank in co-operation with other development partners and non-governmental agencies, carried out in more than 14 countries globally. In Ghana, the first phase of the survey, focusing on adults in urban communities, was carried out in co-operation with the University of Ghana's Institute of Statistical, Social, and

The task content measures calculated from the survey data are consistent with those defined using O*NET (Hardy et al. 2018a; Lewandowski et al. 2019). The definition follows the original approach of Autor et al. (2003), which has since been picked up by numerous studies (Acemoglu and Autor 2011; Handel 2012; Hardy et al. 2018b; Lo Bello et al. 2019; Spitz-Oener 2006). We concentrate our analysis on four different task measures, listed in Table 1.

Table 1: Task items in O*NET used to calculate task content measures

Non-routine cognitive analytical	Non-routine cognitive interpersonal	Routine cognitive	Routine manual
Analysing data/information Thinking creatively Interpreting information for others	Establishing and maintaining personal relationships Guiding, directing, and motivating subordinates Coaching/developing others	Importance of repeating the same tasks Importance of being exact or accurate Structured vs unstructured work (reverse)	Operating vehicles, mechanized devices, or equipment Spend time using hands to handle, control, or feel objects, tools, or controls Manual dexterity Spatial orientation

Source: authors' compilation based on Autor et al. (2003).

Following the previous literature (Autor and Dorn 2009, 2013; Goos et al. 2014), we combine the four constructed task measures into a composite RTI measure using the following formula:

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

where $r_{cognitive}$, r_{manual}, $nr_{analytical}$, and $nr_{personal}$ are the routine cognitive, routine manual, non-routine cognitive analytical, and non-routine cognitive personal task levels, respectively.[3] In contrast to the original approach of Autor and Dorn (2009, 2013), our definition omits non-routine manual tasks from the analysis, because previous studies (Hardy et al. 2016; Lewandowski et al. 2019) have raised doubts concerning its interpretation and have shown that routine and non-routine manual tasks tend to be highly correlated.

We match the O*NET and survey task content measures to the GLSS survey data at the occupational level, using ISCO-88 occupational units at the three-digit and two-digit levels respectively. For details on the coding of occupations, please see Appendix A.

2.2 Linking distributional changes and the task composition of occupations

In this paper, we aim to study the relationship between changes in employment and in earnings, on the one hand, and in the task composition of occupations, on the other. Below we provide condensed snapshots of each of the three main approaches used to investigate these changes for each of the two subperiods—from 2005/06 to 2012/13 and 2012/13 to 2016/17—as well as over the entire period from 2005/06 to 2016/17. For a detailed description of the methods used, please refer to the online Methodological Appendix.

First, as a simple test for job polarization, we regress the log change in employment shares by subperiod on initial log mean weekly earnings (and its square) at the three-digit occupational level,

Economic Research (ISSER), the Ministry of Education, the Council for Technical and Vocational Education and Training (COTVET), and the Ghana Statistical Service (GSS).

[3] For each task, the lowest score in the sample is added to the scores of all individuals, plus 0.1, to avoid non-positive values in the logarithm.

testing the significance of the parameters (Goos and Manning 2007; Sebastián 2018a). We repeat the same exercise with log change in earnings as the dependent variable (Sebastián 2018b). Both equations are estimated by weighting each occupation by its initial employment share to avoid results being biased by compositional changes in small occupation groups. Similarly, in a next step, we fit a quadratic regression—at the three-digit occupational level—of the log change in employment share on the initial level of routine intensity (Sebastián 2018a). Again, we repeat the same exercise with log change in earnings as the dependent variable.

Second, we estimate the contribution of inequality within and between occupations to the overall Gini index in each survey year using the Shapley decomposition technique (Shorrocks 2013). Notably, differences in the average earnings between occupations can affect overall inequality via two different channels. First, changes in the structure of employment can affect inequality trends. For example, if middle-income occupations decrease in size and low- and high-income groups expand while the earnings differences between occupations remain stable, overall inequality will rise. Second, changes in the earnings gap between occupations may also impact the overall distribution of earnings. If, for example, incomes grow faster in high-paying occupations than in low-paying occupations while the structure of employment remains unchanged, this will result in an increase in overall earnings inequality. Therefore, we repeat the analysis with counterfactual distributions in which either the occupational shares or the occupational means are kept constant, to check whether it is changes in the distribution of employment or changes in earnings that explain the trend. To further explore the relevance of the task composition of occupations in explaining trends in inequality between occupations, we calculate the concentration index for the distribution of average earnings by occupations, where occupations are sorted by RTI instead of by average earnings.[4] Both indices are identical when there is perfect correlation between average earnings and RTI. The ratio between the concentration and the Gini index is a measure of the association between RTI and average earnings (based on the Gini metrics).

Third, in a final step, we follow the estimation methodology developed by Firpo et al. (2007, 2009) to quantify the role played by different variables at different points of the earnings distribution in determining inequality trends over time. The original approach presents an extension of the Oaxaca-Blinder decomposition method, where each variable's contribution to the change in earnings is decomposed into a 'composition' effect and a 'wage structure' effect at each percentile of the earnings distribution. The estimation method has been expanded by Fortin et al. (2011) to different functionals of the earnings distribution, including measures of dispersion such as the Gini coefficient (see also Firpo et al. 2011, 2018, for an extensive discussion), which makes this approach particularly useful in the context of our analysis. It allows us to quantify the extent to which inter-temporal changes in inequality can be attributed to changes in the distribution of certain worker characteristics and changes in the labour market remuneration of these characteristics. Technically, the estimation strategy is performed in two stages. At the first stage, distributional changes are divided into an earnings structure effect and a composition effect using a reweighting method approach, where the weights are parametrically estimated. In the second stage, the two components are further subdivided into the contribution of different explanatory variables defined at the individual level using recentred influence function (RIF) regressions. The

[4] The concentration index is defined as twice the area between the concentration curve and the diagonal (while the Gini index is twice the area between the Lorenz curve and the diagonal). While the Lorenz curve plots the cumulative distribution of occupational earnings for each cumulative proportion of employment, with occupations sorted by mean earnings, the concentration curve does the same but with workers sorted by RTI instead. Unlike the Lorenz curve, the concentration curve is not necessarily convex and may fall above the diagonal.

main factors considered here for the Ghana case are the role of workers' education and occupational RTI along other demographic characteristics such as age, gender, and ethnicity.[5]

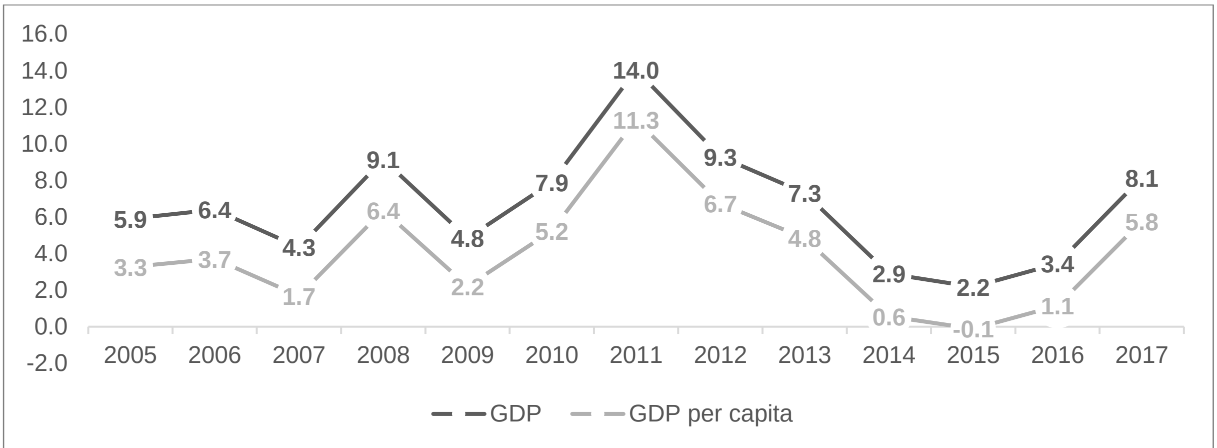
3 Employment trends and earnings inequality

3.1 Economic context

Ghana has made remarkable progress, being recognized as one of the 'most notable success stories' in Sub-Saharan Africa (McKay et al. 2016: 85). It has managed a peaceful democratic transition, has maintained democratic stability, and has experienced strong and robust economic growth over the past three decades, attaining lower-middle-income status in 2007. Between 2005 and 2017, Ghana's gross domestic product (GDP) grew at an average annual rate of 6.6 per cent (see Figure 1). Over the same time period, GDP per capita expanded from GHC3,091 to GHC4,994, growing at an average annual rate of 4.1 per cent, with the highest growth rate being recorded in 2011 (11.3 per cent) and the lowest in 2015 (−0.1 per cent).

During the growth spurt experienced around 2011, Ghana was one of only seven countries in the world, and the only country in Sub-Saharan Africa, to achieve double-digit economic growth (IMF 2012). Importantly, this impressive growth performance is largely attributable to the discovery of oil and gas around that time, adding to the country's traditional main exports of gold and cocoa. Macroeconomic conditions worsened after 2013 in reaction to a fall in oil prices, weaker fiscal and monetary policies, and electricity rationing (GSS 2018b), which slowed GDP growth to around 3 per cent between 2014 and 2016, picking up again in 2017 (see Figure 1).

Figure 1: Annual growth rates of real GDP and real GDP per capita, 2005–17



Source: authors' graphical representation based on World Bank national accounts data (World Bank 2019).

Crude oil exports, mining, and financial intermediation—all sectors with a low labour absorption capacity—were the main factors driving economic growth in Ghana in the 2000s, while the labour-intensive sectors of agriculture and manufacturing grew much more slowly. In consequence,

[5] Covariates are defined as follows: age group (15–24, 25–44 [omitted], 45–64), gender (female, male [omitted]) education level (none, preschool, primary, lower-secondary [omitted], upper-secondary, post-secondary, tertiary), ethnicity (Ashanti-Akan [omitted], Mole-Dagbon, Ewe, Ga-Dangme, Gurma, Guan, Grusi, Mande, other groups), RTI (country-specific or O*NET) in occupation at two-digit level. We included interactions between age, gender, and education.

employment growth in Ghana has not kept up with its economic growth and the structure of the economy remains highly informal (Aryeetey and Baah-Boateng 2016).[6] Importantly, the country's impressive growth rates and its shift away from the dominance of agriculture to services contributing the largest share to national output should not be interpreted as evidence of significant structural transformation (Aryeetey and Baah-Boateng 2016; McKay and Aryeetey 2004). Despite its declining share in the economy, agriculture remains the major source of employment in Ghana, followed by low-value service activities in the informal sector, which accounted for the largest proportion of newly created jobs over the past decades (Aryeetey and Baah-Boateng 2016).

Ghana's strong economic performance—accompanied by several social intervention programmes implemented over the last two decades (GSS 2018b)—can be associated with a significant reduction in consumption poverty. As can be seen from Table 2, the proportion of Ghanaians living below the international poverty line, set at US$1.90 a day (2011 purchasing power parity/PPP) reduced by three-quarters from close to 50 per cent in the early 1990s to 24.5 per cent in 2005/06 and 12 per cent in 2012/13, one of the lowest poverty rates in the region (World Bank 2019). Similarly, the incidence of poverty measured by national standards reduced from 31.9 to 24.2 per cent over the seven-year period from 2005/06 to 2012/13. However, poverty reduction stalled in subsequent years. As Table 2 shows, the country recently witnessed a slight increase in extreme poverty and in the incidence of poverty in rural areas, with the rural poverty headcount in 2016/17 being five times higher than that of urban areas. Historically, there has been a large regional variation in the incidence of poverty—the Northern Region accounting for the highest share of people living in poverty, while Greater Accra contributes the lowest share—and regional gaps have widened in recent years. Nonetheless, a disaggregated picture reveals important disparities within regions, including sizeable pockets of poverty even in the better-off regions (GSS 2018b).

Starting from a relatively low level in the 1990s, consumption inequality (based on per capita household consumption) has continuously widened in Ghana, as indicated by an increase in the Gini index of between 5 and 6 points from 1991/92 to 2016/17 (see Table 2). In particular, the rise in inequality over the 12-year period from 2005/06 to 2016/17 has been concentrated largely in rural areas. A comparison of the growth rates in per capita consumption at different points of the wealth distribution suggests that the benefits of growth have not reached households in the poorest quintile (GSS 2018b).

[6] As noted by the International Labour Organization (ILO), employment elasticity of growth has declined from 0.64 in 1992–2000, to 0.52 in 2000–04, and further down to 0.4 in 2004–08 (ILO 2009).

Table 2: Poverty headcount ratio (% of population) and Gini index, 1991/92–2016/17

	World Bank estimate (2011 PPP)		National estimate (upper poverty line)			Gini index
	US$1.90 a day	US$3.20 a day	National	Urban	Rural	
1991/92	49.8	78.6	n.a.	n.a.	n.a.	38.1
1998/99	35.7	63.3	n.a.	n.a.	n.a.	40.8
2005/06	24.5	50.1	31.9	12.4	43.7	42.8
2012/13	12.0	32.5	24.2	10.6	37.9	42.3
2016/17	13.3	30.5	23.4	7.8	39.5	43.5

Note: in Ghana, poverty is measured in terms of household consumption expenditure, covering food and non-food items. The overall cost of living index is adjusted for both differences in relative spatial prices and variation in prices over time within the survey period, using monthly regional consumer price indices (CPIs). The national upper poverty line was estimated at GHC1,314 per adult equivalent per year in 2012/13.

Source: authors' compilation based on World Bank (2019) and national estimates (GSS 2018b).

3.2 Earnings inequality

Earnings inequality among paid employees and non-farm self-employed workers in Ghana, as measured by the Gini index, showed a modest decline from 57.1 in 2005/06 to 56.6 in 2016/17.

However, in line with the trends in household consumption inequality (see Section 3.1 above), we observe striking differences by subperiod. For the first subperiod (2005/06 to 2012/13), in which the economy grew much faster, we find a substantial decline in the Gini index of almost three points (see Table 3). During these years, in relative terms, growth in earnings was strongest at the bottom and weakest at the top of the distribution (see Figure 2). This was followed by a second period (2012/13 to 2016/17) in which the economy kept growing but at a slower pace, with a clear pro-rich pattern. While earnings were shrinking in the bottom quintile, higher earnings percentiles experienced positive growth, resulting in a rise in inequality.

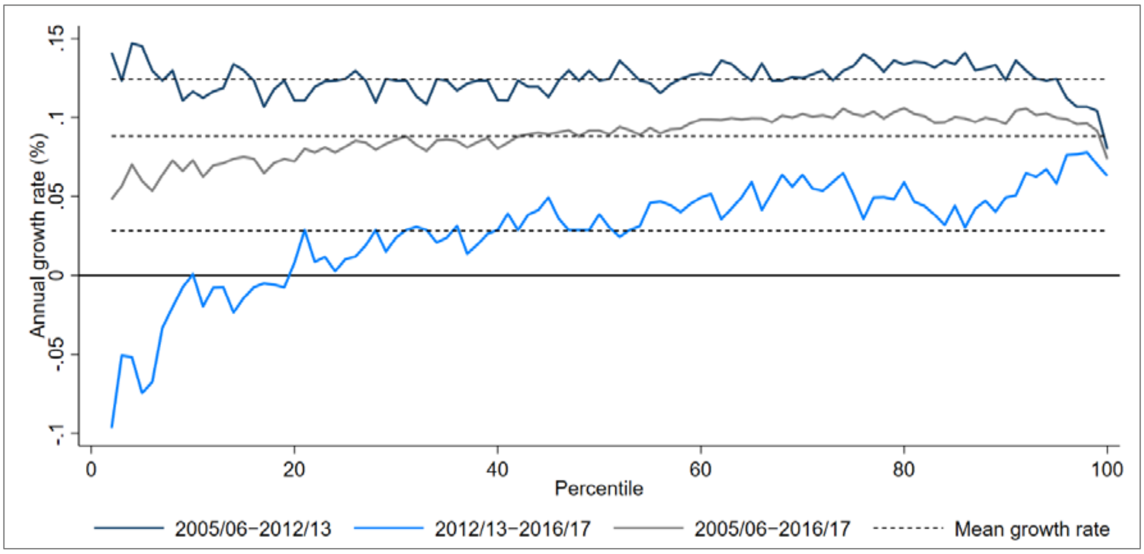
The net pattern over the entire time span shows positive earnings growth across the distribution. The bottom 40 per cent experienced below-average growth rates, and earnings growth was strongest at the upper-middle of the distribution, between the 60th and 95th percentile. At the very top of the distribution, earnings growth was weaker than the national average, resulting in a moderate decline in the Gini index over the full time period.

Table 3: Earnings inequality among paid employees and non-farm self-employed workers, 2005/06–16/17

	Summary indices				Inter-quantile ratios		
	2005/06	2012/13	2016/17		2005/06	2012/13	2016/17
Var (log earn)	1.32	1.26	1.58	ln(q90)-ln(q10)	2.73	2.88	3.16
Gini (log earn)	19.9	16.2	17.0	ln(q90)-ln(q50)	1.28	1.36	1.43
Gini (earn)	57.1	54.4	56.6	ln(q50)-ln(q10)	1.45	1.53	1.73

Source: authors' calculations.

Figure 2: Growth of earnings among paid employees and non-farm self-employed workers, 2005/06–16/17



Source: authors' calculations.

3.3 Structural change in employment

Over the period from 2005/06 to 2016/17, Ghana experienced significant structural changes, characterized by a pronounced move of employment away from agriculture toward services, which was most pronounced in the first subperiod up to 2012/13. As can be seen from Table 4, this was accompanied by an important expansion of the share of paid employees (from 19 to 30 per cent) in the workforce—observed for both men (from 29 to 41 per cent) and women (from 9 to 19 per cent)—along with a decline in agricultural self-employment (from 53 to 37 per cent).[7]

Table 4: Distribution of workers by status in employment (%), 2005/06–16/17

	Male workers			Female workers			All workers		
Status in employment	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17
Paid employees	29.13	35.05	40.87	9.27	14.11	18.91	18.8	24.27	29.79
Non-agriculture									
Self-emp. w. employees	3.16	4.77	3.67	2.77	4.71	3.42	2.96	4.74	3.55
Self-emp. w/o employees	11.83	12.1	13.75	34.78	32.61	37.47	23.77	22.66	25.72
Unpaid family workers	0.62	2.3	2.38	2.08	4.93	5.72	1.38	3.65	4.07
Subtotal	15.61	19.17	19.8	39.63	42.25	46.61	28.11	31.05	33.34
Agriculture									
Self-emp. w. employees	2.28	2.14	0.96	0.88	1.11	0.29	1.55	1.61	0.62
Self-emp. w/o employees	40.79	29.28	28.08	22.16	18.3	17.09	31.09	23.63	22.53
Unpaid family workers	12.19	14.37	10.29	28.06	24.24	17.09	20.45	19.45	13.72
Subtotal	55.26	45.79	39.33	51.1	43.65	34.47	53.09	44.69	36.87

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

[7] When we restrict the sample to paid employees and non-farm self-employed workers (i.e., exclude agricultural self-employment), we observe a rise in the relative share of paid employees (from 40 to 47 per cent), especially among women (from 19 to 29 per cent) but also men (from 65 to 67 per cent), along a decline in the relative weight of non-farm self-employment.

As in other Sub-Saharan African countries, the shift away from agriculture was associated with a considerable increase in the relative share of services, while the growth of employment in the industry sector has been comparatively slow. Particularly during the first subperiod (2005/06 to 2012/13), Ghana witnessed a sharp drop in the share of employment in agriculture (from 56 to 47 per cent), but also a decline in manufacturing (from 11 to 8 per cent), while the employment share expanded in construction, mining, and a large range of services such as trade, transport, hotels and restaurants, and other services. During the second subperiod (2005/06 to 2012/13), the agriculture share continued to decline but at a slower pace (from 47 to 44 per cent), whereas the manufacturing sector recovered part of its initial employment levels, and construction continued to expand. In addition, the country saw an outstanding expansion particularly of high-skilled services such as education and public administration (see Table 5). Accordingly, the formality rate among paid employees and non-farm self-employed workers fell from 30 per cent in 2005/06 to 26 per cent in 2012/13 and increased thereafter to 34 per cent in 2016/17.

Changes in the sectoral composition of employment are strongly related to inequality. Evidence for Sub-Saharan economies suggests that inequality rises with growth in sectors characterized by high asset concentration, high capital absorption, and skilled-labour intensity, such as mining, finance, insurance, and real estate, and tend to decline with growth in labour-intensive sectors such as manufacturing, construction, and agriculture (Odusola et al. 2017). Existing research also suggests that employment growth in manufacturing tends to reduce income inequality, while a shift toward service sector employment tends to increase inequality in structurally developing countries (Baymul and Sen 2020), especially if driven primarily by the informal sector. Based on this evidence, we would expect that these structural changes in the sectoral composition of employment in Ghana would tend to be generally inequality-enhancing, being at odds with the reduction in inequality observed in the first subperiod.

Table 5: Distribution of workers by industry (%), 2005/06–16/17

	All workers			Paid employees and non-farm self-employed		
Industries	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17
Agriculture and fishing	55.62	46.94	43.69	6.27	3.37	3.49
Mining and quarrying	0.77	1.70	1.58	1.72	3.20	2.51
Manufacturing	11.02	8.20	9.75	22.66	14.05	17.19
Electricity, gas, and water supply	0.21	0.43	0.43	0.46	0.87	0.66
Construction	1.78	3.18	4.20	3.92	6.14	7.05
Wholesale and retail trade	16.18	19.80	17.04	34.15	34.14	32.09
Hotels and restaurants	1.96	3.82	2.77	4.01	6.46	4.72
Transport, storage, and communications	2.97	4.34	4.23	6.26	8.50	6.86
Financial intermediation	0.39	0.69	1.17	0.82	1.55	1.82
Real estate, renting, and business activities	0.86	0.07	0.11	1.85	0.12	0.27
Public administration and defence	1.46	0.76	2.05	3.23	1.61	3.14
Education	3.46	3.52	6.17	7.54	7.38	9.30
Health and social work	0.90	1.06	1.74	1.91	2.13	2.64
Other services	2.43	5.51	5.07	5.20	10.47	8.26

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

In line with the sectoral changes in the occupational structure discussed above, in both subperiods we observe a movement towards jobs demanding higher skills, including managers (ISCO 1) and professionals (ISCO 2), which during the first subperiod was counterbalanced by a significant increase in the share of service and sales workers (ISCO 5),[8] who tend to be low to medium skilled, as well as a rise in low-skilled elementary occupations (see Table 6).

Table 6: Distribution of workers by occupation (%), 2005/06–16/17

	All workers			Paid employees and non-farm self-employed		
Occupations (ISCO-88)	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17
1 Managers	0.49	1.48	1.86	1.07	2.78	3.12
2 Professionals	3.25	4.52	7.16	7.06	9.55	10.94
3 Technicians and associate professionals	2.27	2.00	2.26	4.78	3.77	3.82
4 Clerical support workers	1.31	1.41	1.79	2.81	2.94	2.75
5 Services and sales workers	14.17	19.24	18.48	29.58	34.02	33.63
6 Skilled agricultural, forestry, and fishery	53.31	46.27	42.04	3.36	2.44	2.25
7 Craft and related trades workers	13.20	10.18	10.81	27.65	17.98	19.02
8 Plant and machine operators and assemblers	3.55	4.28	5.24	7.54	8.15	8.26
9 Elementary occupations	8.45	10.62	10.36	16.14	18.37	16.20

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

These changes in the employment structure also imply a shift towards more non-routine occupations. The average RTI declined over the full time period regardless of whether it is measured using O*NET or, alternatively, the country-specific survey-based measure (see Table 7).[9]

Table 7: Average routine-task intensity (RTI), 2005/06–16/17

	All workers			Paid employees and non-farm self-employed		
RTI measure	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17
Country-specific	0.70	0.68	0.62	0.70	0.67	0.65
O*NET	0.33	0.21	0.12	0.34	0.20	0.14

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

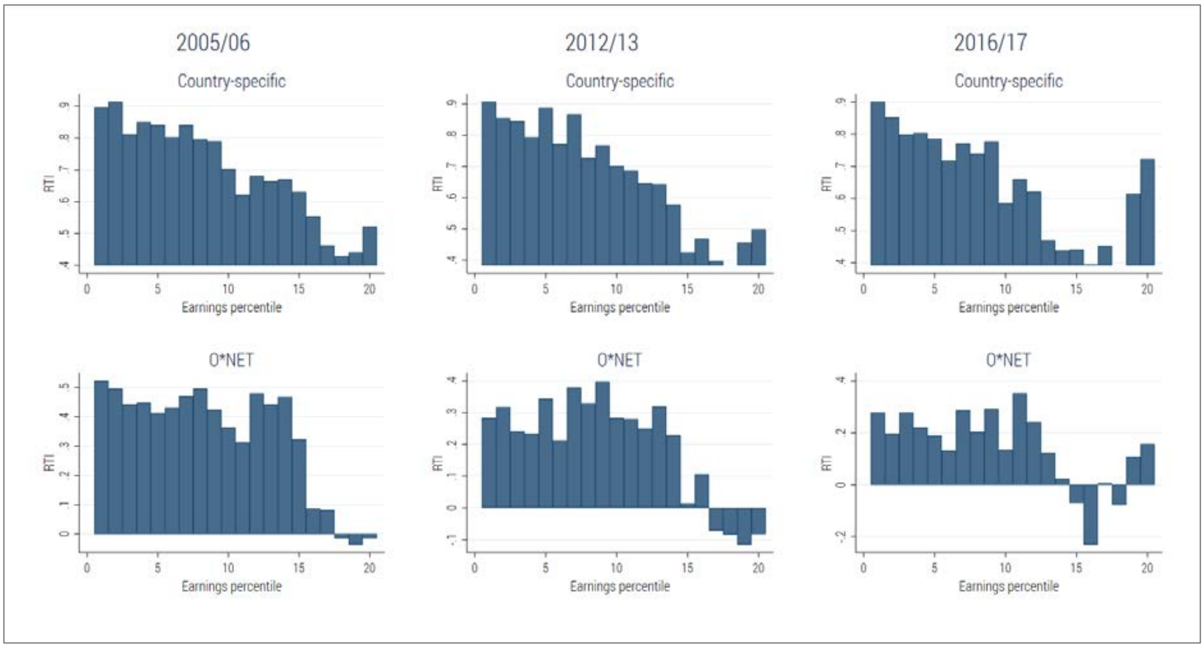
As Figure 3 shows, the country-specific RTI measure is clearly negatively correlated with earnings percentiles, except at the very top. This last feature is accentuated in the last wave, with an increase in the share of routine occupations among top earners. The relationship with respect to the O*NET RTI measure is weaker, although the concentration of routine tasks is still highest among the bottom 5 per cent, and declines sharply at the top in the first wave. The first feature vanishes in the second wave, when the relationship turns into a U-shaped curve, with the routine-task-intensive occupations dominating in the middle of the earnings distribution. The graphical evidence suggests that the relationship between the routine-task intensity of occupations and earnings has weakened over time. While those at the bottom of the distribution tend to be in highly

[8] We expect many of the workers in this occupational group to engage in informal sector activities, such as petty trading, shop-keeping, and street vending.

[9] The decline in RTI is robust across alternative specifications. We obtained similar time trends when using ISCO-08 classifications for 2012/13 and 2016/17 (instead of recoding to ISCO-88) and when aggregating occupations to the three-digit (instead of two-digit) level (results available from the authors upon request).

routinized jobs, those at the top of the occupation are not necessarily in occupations with the lowest routine-task intensity.

Figure 3: Routine-task intensity by earnings percentile, 2005/06–16/17



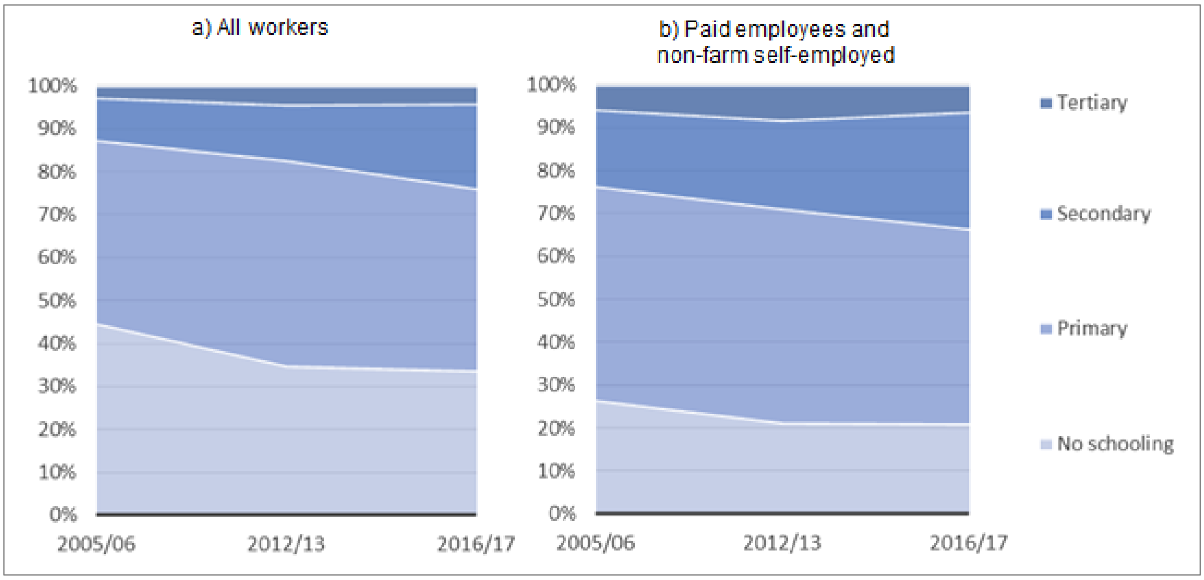
Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

3.4 Skills supply and education premium

The main driver of earnings inequality trends worldwide is usually the education premium, in line with the well-known 'race between technology and education' that Goldin and Katz (2010) described for the United States. As long as a surge in the demand for higher skills, whether due to the exposure to technical change or international trade, is not followed by a similar increase in the supply of skilled workers, earnings will tend to grow faster for the highly educated as they become relatively scarcer. Ceteris paribus, this leads to a rise in the skill premium—the ratio of high-skilled to low-skilled wages—inducing a rise in earnings inequality between workers. Similarly, inequality will fall in a scenario in which, as in several developing countries, the expansion in the supply of skills as better-educated new generations enter the labour market outpaces a weak demand for higher skills in the absence of true structural transformation. Gradín et al. (forthcoming) show evidence of the role of the skill premium in driving the trends in inequality in Brazil, China, India, Mexico, and South Africa during the last decades.

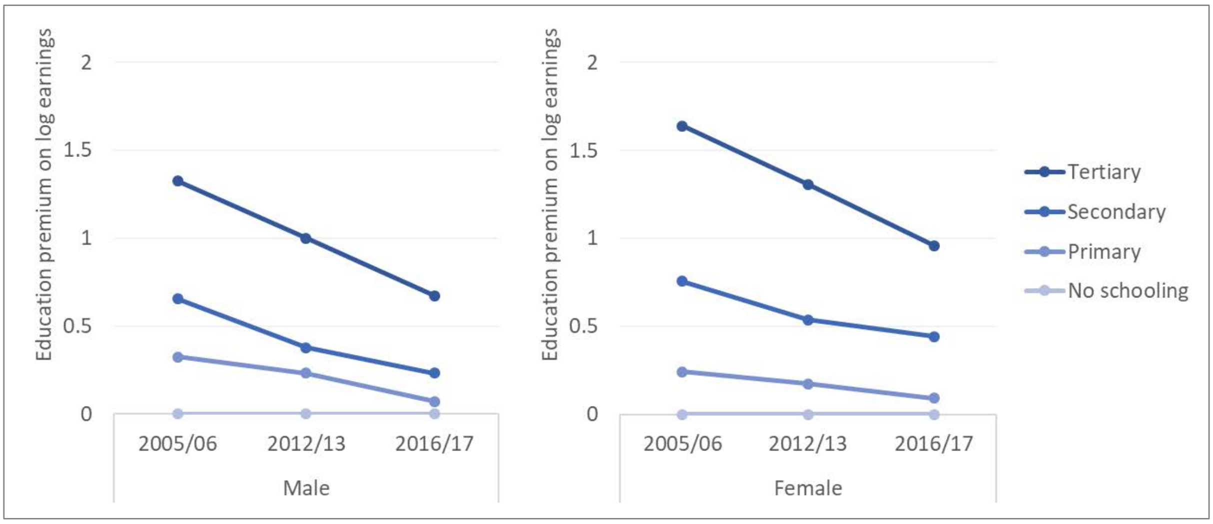
This second scenario seems to better fit the case of Ghana during the first subperiod. From 2005/06 to 2012/13, the fall in inequality was mirrored by a substantial decline in the education premium at all levels, and for both men and women, following a general improvement in the level of education of workers (see Figures 4 and 5). However, it is worth noticing that the education premium continued falling during the second period up to 2016/17. The rise in earnings inequality over this later period thus must have been explained by other factors.

Figure 4: Education levels of among paid employees and non-farm self-employed workers, 2005/06–16/17



Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

Figure 5: Education premium by gender and level of education, 2005/06–16/17



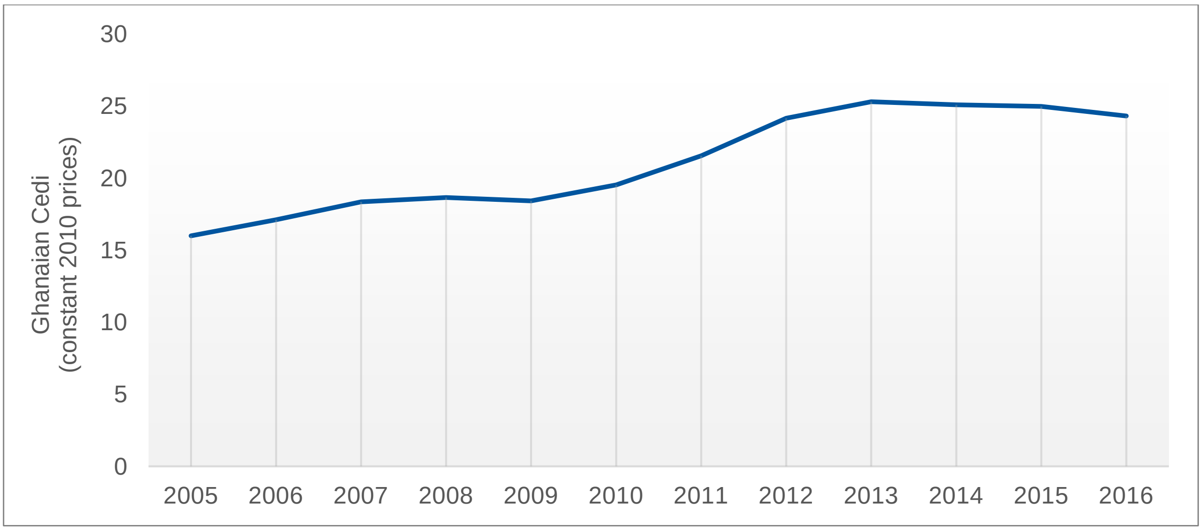
Note: log weekly earnings are regressed in each year separately by gender on dummy variables for three education levels (tertiary, secondary, primary, with no schooling as base category), two age groups (ages 15 to 24 years and 45 to 64 years, with 25 to 44 years as base category), seven region dummies (with Greater Accra as base category), eight ethnic groups (with Ashanti-Akan as base category), and occupation units at the ISCO-88 two-digit level (with salespersons [ISCO 52] as base category). The figure shows the coefficient estimates on the education categories, which directly measure the returns to attaining a higher level of education in terms of (log) weekly earnings (i.e., the education premium) across survey waves separately by gender.

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

3.5 Minimum wage

Additionally, institutional factors might help to explain the different inequality trends observed in the two subperiods. In the Ghana context, it is noteworthy that there was a substantial increase in the national minimum wage in real terms during the first subperiod (2005/06 to 2012/13), raising the floor of the distribution, while minimum wages stagnated in the second subperiod (2012/13 to 2012/13), even showing a moderate decline in real terms (see Figure 6).

Figure 6: Real weekly minimum wage (GHC), 2005–16



Note: figures have been deflated to constant 2010 prices using the Ghana CPI provided by the International Monetary Fund, International Financial Statistics, and data files.

Source: authors' calculations based on ILOSTAT data from 1995 to 2013 (ILO 2020) and Mywage.org/Ghana data from 2013 to 2016 (Mywage.org/Ghana 2020).

4 Role of tasks and skills in changing earnings inequality

The aim of this section is to investigate the main drivers of the trends in earnings inequality in Ghana by subperiod. As discussed in Section 3, we find a decline in earnings inequality during the first subperiod (2005/06 to 12/13), characterized by strong pro-poor growth; and a rise in inequality during the second subperiod (2012/13 to 16/17), characterized by slower growth displaying a clear pro-rich pattern. The descriptive statistics presented in the previous section furthermore pointed to a decline in the education premium over the full period, which may be associated with the fall in inequality in the first subperiod but cannot explain the subsequent rise. Moreover, observed shifts in the occupational structure seemed to counteract the inequality trends. In this section, we want to dig deeper into the contributions of these and other factors in explaining the trends in inequality. Particularly, we want to understand to what extent changes in earnings inequality were the result of changes in the nature of jobs performed by workers.

For this, we will first analyse the presence of polarization patterns in terms of either employment or earnings in Ghana with respect to both initial earnings in a job and RTI.

4.1 Job and earnings polarization

In the presence of job polarization, we would expect to see employment growing more strongly in both low- and high-paying occupations while declining in middle-paying occupations, producing a hollowing out of middle-class jobs. Similarly, in the presence of earnings polarization, we would expect to see earnings growing more strongly in jobs at both ends of the earnings distribution at the expense of the middle.

As previously documented, Ghana followed other developed and developing countries and experienced a decline in the routinization of jobs that might follow a polarizing trend. However, there are reasons to believe that this may not apply to Ghana given its position as a middle-income country, as well as its insertion in the global value chain, characterized by a weak manufacturing industry and an expanding oil sector, along with the relatively minor transformation of the economy, in which agriculture remains key despite the large shift of workers to the service sector.

Given that polarization can be represented by a U-shaped pattern in the relationship between changes in employment or earnings and initial earnings across occupations, it can be tested either graphically or using a simple econometric test of a quadratic relationship. The former is done by regressing—at the three-digit occupational level—the log change in employment share and the change in log mean earnings between survey waves, on initial log mean weekly earnings and its square, testing the significance of the parameters (Goos and Manning 2007; Sebastián 2018b). Polarization in this context implies that the coefficient of log earnings is negative while the coefficient of its squared value is positive. Although the impacts of these polarization trends on inequality are not straightforward, they are mostly associated with periods of increasing inequality.

Table 8 summarizes the results for Ghana. The first period in Ghana was characterized by declining inequality, and we actually observe an inverted-U-shaped pattern, a sign of depolarization, with both earnings and employment growing faster at the middle of the distribution. However, the quadratic term in the regression is only statistically significant with regard to the change in log mean earnings.

The graphs in Figure 7 help to visualize the actual changes. The inverted-U pattern is clearly visible in the bottom panel, showing changes in earnings. However, while there was a large decline in employment at the bottom of the distribution, the improvement in the middle was less uniform than that found for earnings, and there was an increase also at the top.

The second period, however, was characterized by increasing inequality, and therefore it is more likely to show a polarizing pattern. Indeed, we observe a polarizing trend in both employment and earnings, although this is not statistically significant in the econometric regressions (see Table 8). The graphs show that changes in employment occurred mostly in the middle, expanding employment in the lower middle at the expense of the upper-middle. Changes in earnings tended to favour the lowest-paying jobs, which seems paradoxical in a period of growing inequality. This indicates that rising inequality was not the result of disequalizing changes in earnings across occupations but was due to other factors, which will be explored in more detail in the next subsection.

When splitting the sample by workers' formality status, we find that the depolarizing employment shift towards middle-income occupations in the first period was more pronounced in the informal sector. During this time, the earnings of informal workers tended to grow faster in low-paying occupations, while the earnings of formal workers grew fastest in middle-paying occupations. For the second period, we find some evidence of a polarizing U-shaped trend in formal employment, even though the quadratic term is not statistically significant (see Appendix B, Table B1 and Figure B1).

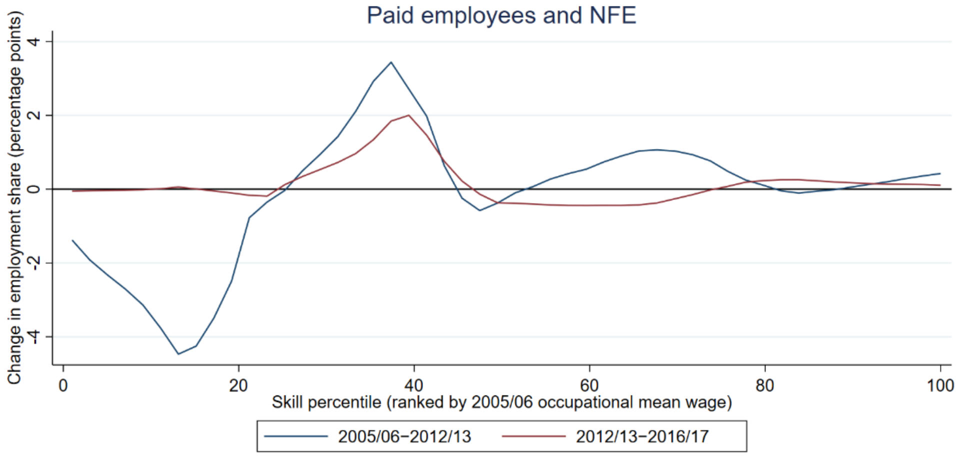
Table 8: Check for employment and earnings polarization, 2005/06–16/17

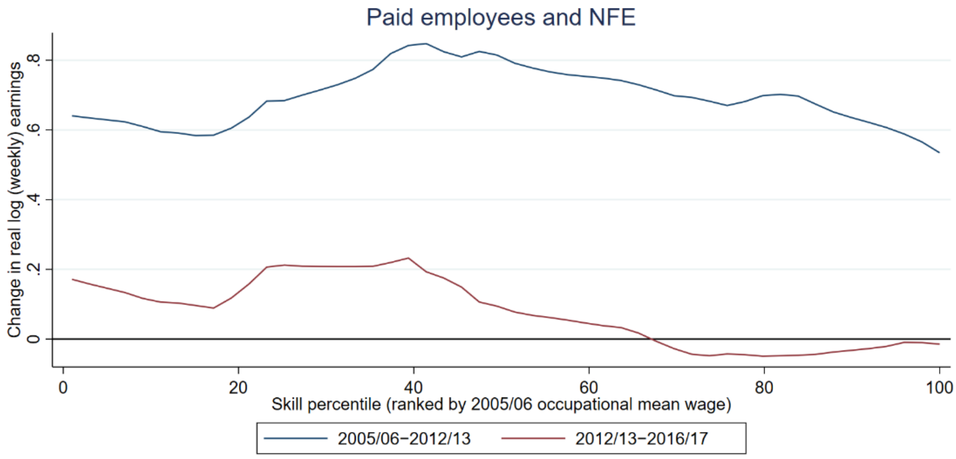
	Log change in employment share			Change in log mean earnings		
	2005/06–12/13	2012/13–16/17	2005/06–16/17	2005/06–12/13	2012/13–16/17	2005/06–16/17
(log) mean weekly earnings (t−1)	3.731*	−0.891	2.292	0.847**	−0.640	−0.424
	(2.227)	(0.909)	(2.131)	(0.370)	(0.971)	(0.591)
Sq. (log) mean weekly earnings (t−1)	−0.471	0.110	−0.260	−0.157***	0.043	−0.009
	(0.290)	(0.110)	(0.271)	(0.052)	(0.119)	(0.080)
Constant	−7.182*	1.728	−4.767	−0.369	1.905	2.219**
	(4.230)	(1.840)	(4.120)	(0.647)	(1.936)	(1.057)
Observations	104	97	97	104	97	97
Adj. R-squared	0.086	−0.014	0.075	0.175	0.198	0.331

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

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

Figure 7: Changes in employment and earnings across skill percentiles





Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

In the industrialized nations, the main hypothesis about what is behind polarization trends is that they are the result of earnings and employment growing faster in non-routine manual and cognitive jobs, which in countries such as the US tend to be allocated at the two extremes of the earnings distribution, while growth is slower in middle-income routine jobs that are most affected by automation and international trade competition. As shown in Figure 3 in Section 3.3 above, in Ghana the relationship between RTI and earnings is less straightforward and tends to depend on the point in time and measure used. To check the extent to which changes in employment and earnings in Ghana were concentrated in jobs involving more or less routine-intensive tasks, we also fit a quadratic regression—at the three-digit occupational level—of the log change in employment share and of the log change in earnings on the level of routine intensity, using the country-specific RTI measure (see Table 9) and the O*NET RTI measure (see Table 10).

Overall, we find that the routine-task content of occupations explains only a small share of the variance in changes in both employment and earnings at the occupational level. We find some tentative evidence that employment declined and earnings increased in occupations with higher intensity in routine tasks (especially when measured by O*NET), but the patterns are only weakly statistically significant.

Table 9: Correlation between country-specific RTI and changes in employment and earnings, 2005/06–16/17

	Log change in employment share			Change in (log) mean earnings		
	2005/06–12/13	2012/13–16/17	2005/06–16/17	2005/06–12/13	2012/13–16/17	2005/06–16/17
Country-specific RTI	−0.534	−0.072	−0.634	0.102	0.104	0.357*
	(0.414)	(0.095)	(0.426)	(0.093)	(0.103)	(0.186)
Sq. country-specific RTI	0.314	0.057	0.479	−0.065	−0.012	−0.137
	(0.297)	(0.055)	(0.294)	(0.081)	(0.059)	(0.149)
Constant	−0.168	−0.044	−0.176	0.700***	0.029	0.700***
	(0.175)	(0.064)	(0.189)	(0.044)	(0.059)	(0.073)
Observations	104	97	97	104	97	97
Adj. R-squared	0.007	−0.015	0.027	−0.007	0.011	0.074

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

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

Table 10: Correlation between O*NET RTI and changes in employment and earnings, 2005/06–16/17

	Log change in employment share			Change in (log) mean earnings		
	2005/06–12/13	2012/13–16/17	2005/06–16/17	2005/06–12/13	2012/13–16/17	2005/06–16/17
O*NET RTI	−0.303	−0.057	−0.357*	0.029	0.022	0.095*
	(0.193)	(0.041)	(0.180)	(0.027)	(0.039)	(0.054)
Sq. O*NET RTI	−0.026	−0.011	−0.043	0.003	−0.009	−0.004
	(0.067)	(0.011)	(0.061)	(0.013)	(0.014)	(0.029)
Constant	−0.175	−0.027	−0.089	0.710***	0.094	0.822***
	(0.168)	(0.050)	(0.154)	(0.045)	(0.062)	(0.088)
Observations	104	97	97	104	97	97
Adj. R-squared	0.073	0.010	0.142	−0.008	−0.009	0.032

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

Source: Authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

When splitting the sample by workers' formality status, we find a statistically significant shift away from routine jobs in the formal sector over the first period, while for the entire period the country-specific RTI measure points to a modestly polarizing U-shaped pattern (see Appendix B, Table B2 and Figure B2). The positive relationship between the routine content of jobs and earnings growth is statistically significant for informal workers in the first period, which is mainly explained by the highly mixed growth rates in less-routinized occupations.

4.2 Earnings inequality across occupations and its relationship to routine-task content

To further assess the role of tasks performed by workers in their jobs in explaining observed inequality trends, we turn our attention to the distribution of mean earnings by occupation. The average pay by occupation reflects the labour market rewards attached to each job. Differences between occupations do not necessarily perfectly reflect differentials in skill requirements and productivity but can also be influenced by other job characteristics, such as working conditions, sectoral differences (e.g., wage differentials between public and private sector workers), and the type of tasks being performed.

If changes in the rewards of certain occupations help to explain the trends in earnings inequality, this would be reflected in the gaps in average earnings between occupations. If, however, inequality changes are explained by other factors not related to the characteristics of occupations, such as differences in skills or other productivity-related attributes among workers performing similar jobs, this would be reflected in within-occupation inequality driving the overall earnings inequality patterns.

According to the Shapley decomposition that allows us to disaggregate the total Gini index into the contribution of inequality between and within occupations, we find that differences in average earnings across occupations explain 19 per cent of overall earnings inequality at the beginning of our study period (based on ISCO-88, two digits).[10] While this share remained at a similar level during the first period, it declined substantially thereafter, accounting for only 11 per cent of overall inequality in the final year. This implies that differences in earnings within occupations explain the bulk of earnings inequality and that this feature has intensified over time (see Table 11). This finding is robust across alternative specifications. When distinguishing between formal and informal workers in each occupation, differences in average earnings across occupational groups account for a higher proportion but with a similar trend (see Table B4, Appendix B). Even when additionally disaggregating occupations to the three-digit level, inequality within occupational groups still accounts for the largest contribution to total inequality: 27 per cent of overall earnings inequality is explained by between-occupation differences at the beginning and 23 per cent at the end of our study period (see Table B5, Appendix B).[11] A further inspection of these changes reveals that the main driver for rising inequality within occupations in the second period was 523, 'Stall and market salespersons', which increased in size (from 18.7 to 21.1 per cent) and inequality (from 60.2 to 63.4). This is consistent with new workers joining the occupation falling at the bottom of the distribution, as one would expect from the type of structural transformation experienced by Ghana. This occupation witnessed changes in the same direction during the first period, but this

[10] This figure should not be confused with the ratio of between-occupation and total inequality, which will tend to be higher but does not clearly reflect the contribution of differences in earnings by occupation to inequality, as discussed in the Methodological Appendix. This ratio was 34, 32, and 20 per cent in each year (ISCO-88, two digits) and 39, 38, and 32 (ISCO-88, three digits), showing a similar trend to the indicator discussed in the main text.

[11] There was also an intense decline in inequality between workers by educational level (eight categories, from no education to tertiary education) over the entire period, from explaining 20 per cent of initial overall inequality to explaining 14 and 9 per cent in later years.

was more than compensated for by opposite trends in other occupations (such as 741, 'Food processing and related trades workers', which declined both in size and inequality).

Accordingly, while the initial reduction in inequality was explained in similar proportions by earnings inequality declining between and within occupations (maintaining the relative contributions), the subsequent increase in inequality was entirely driven by a rise in inequality within occupations, partially offset by the continuation of the decline in between-occupation inequality as previously discussed.

Table 11: Gini index decomposed into inequality between and within occupations, 2005/06–16/17

	Actual			Shares constant			Means constant		
	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17
1 Overall Gini	0.571	0.544	0.566	0.571	0.551	0.575	0.571	0.566	0.587
Shapley decomposition									
2 Between-occupation	0.110	0.096	0.062	0.110	0.109	0.064	0.110	0.136	0.134
% ratio	19%	18%	11%	19 %	20 %	11 %	19 %	24 %	23 %
3 Within-occupation	0.462	0.448	0.504	0.462	0.442	0.512	0.462	0.430	0.453
% ratio	81%	82%	89%	81 %	80 %	89 %	81 %	76 %	77 %

Note: ISCO-88, two digits.

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

To better understand the drivers behind the decline in inequality between occupations, we disentangle the direct role of changes in the composition of employment by occupation from the role of changes in mean earnings by occupations. As explained in Section 2.2 and the Methodological Appendix, we do this by analysing two counterfactual situations in which either occupation shares or mean earnings are held constant. Table 12 reports the Shapley decomposition results.

Table 12: Change in the Gini index decomposed into the contribution of changes in employment shares and in mean earnings (Shapley decomposition based on Table 11), 2005/06–16/17

	2005/06–12/13	2012/13–16/17	2005/06–16/17
Change in employment shares (mean earnings constant)	0.006	0.018	0.024
Change in mean earnings (employment shares constant)	−0.020	−0.052	−0.072
Total change	−0.014	−0.034	−0.048

Note: ISCO-88, two digits.

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

Our findings show that the decline in between-occupation inequality in both subperiods is entirely due to a narrowing of the gap in average earnings across occupations. We thus detect an equalizing effect associated with changes in the remuneration of job characteristics (e.g., skills and tasks) on the labour market. Contrarily, without this equalizing change in average earnings, inequality between occupations would have increased as a result of changes in employment shares across occupations. Thus, the shifts in the structure of employment across occupations (e.g., movements of workers towards higher-skilled and less-routine occupations) were inequality-enhancing, as confirmed in the Shapley decomposition (Table 12). This finding is robust across alternative specifications, distinguishing between formal and informal employment in each occupation, and disaggregating occupations to the three-digit level (see Tables B6 and B7, Appendix B). Table 12 moreover suggests that both the equalizing effect of changes in mean earnings and the disequalizing effect of changes in the composition of employment were more pronounced in the second subperiod, with the former dominating the latter in both periods, explaining the overall decline in inequality between occupations.

We isolate the effect of RTI, i.e. the extent to which the degree of routinization of occupations is associated with this decline in earnings inequality between occupations, in a first simple approach, by looking at the concentration index. This index measures the extent to which average earnings of occupations tend to systematically increase with less routine intensity of jobs. In fact, the Gini concentration and between-group inequality indices are the same whether sorting occupations by average earnings or from highest to lowest RTI , in which case the concentration ratio (the ratio between both indices) would be 100 per cent.

As can be seen from Table 13, the two occupation rankings are highly similar in the first survey wave, as indicated by the corresponding concentration ratios (varying between 73 per cent using the country-specific measure and 63 per cent using O*NET). However, while the country-specific measure suggests that this relationship further intensified over the first period, we observe a decline in the rank correlation between earnings and the O*NET RTI measure. However, during the second subperiod (and the entire period), the correlation unambiguously declines according to both measures (to a ratio of 46 and 21 per cent respectively), indicating that the relationship between routine intensity of occupations and average earnings has weakened.

This decline likely reflects the fact that although the average RTI tends to be lower for occupations with higher earnings, this relationship is non-monotonic, and the least routine occupations are not necessarily the best-paid ones. This feature is exacerbated during the second subperiod, since there is an increase in the share of relatively routine occupations among the best-paying jobs.

Table 13: Concentration index, 2005/06–16/17

	Actual			Shares constant			Means constant		
	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17
Gini between occupations	0.193	0.174	0.115	0.193	0.194	0.115	0.193	0.232	0.238
Concentration index									
RTI (country-specific)	0.141	0.140	0.053	0.141	0.135	0.046	0.141	0.199	0.205
% ratio	73%	80%	46%	73%	70%	40%	73%	86%	86%
RTI (O*NET)	0.122	0.081	0.025	0.122	0.105	0.029	0.122	0.159	0.162
% ratio	63%	47%	21%	63%	54%	25%	63%	68%	68%

Source: authors’ calculations based on GLSS 5, GLSS 6, and GLSS 7.

4.3 Disentangling inequality drivers: the RIF-regression decomposition

To further investigate the role played by the routine-task content of occupations in shaping inequality, we use a RIF-regression decomposition approach to disentangle the relative importance of routine-task content in occupations, as opposed to the contribution of other competing explanations, particularly skills and demographic factors. The approach also allows us to disentangle whether the effect, if any, is channelled through changes in the composition of employment by occupation (composition effect) or in the associated earnings (wage structure effect). The former accounts for the first-round effect of compositional changes, such as the shift toward less-routine jobs or the increasing level of education among workers, before these changes have an effect on earnings. The latter accounts for the structural changes in earnings—that is, how the labour market retributes worker characteristics. Both effects, however, are interlinked, as the change in the structure of earnings may be the second-round (general equilibrium) effect of the changes in workforce composition. For example, the returns to education may fall as the result of an expansion in the supply of better-educated workers. But identifying which effects are more relevant helps us to better understand the nature of the inequality trend.

The results confirm some of the findings previously described. Changes in the demographic characteristics (i.e., in age composition and female employment) and education levels of the workforce, or in the structure of employment (i.e. the shift of workers towards less-routine occupations, changes in the share of formality), do not seem to directly explain the trend in inequality if the returns to these attributes are kept constant over time. If anything, changes in educational attainment, generally consisting of a rise in education levels (see Section 3.4), point in the opposite direction to the inequality trend. The decline observed in the share of workers in the formal sector in the first period, followed by an increase in the second period, also point in the opposite direction to the general inequality trend. That is, they show a disequalizing effect in the first subperiod, when inequality declined, and an equalizing effect in the second period, when inequality increased.

In consequence, it is the earnings structure effect (i.e., changes over time in the market returns to workers' characteristics, holding their composition constant), that explains the trend in inequality observed in the two examined subperiods. Specifically, the initial decline in inequality can be attributed largely to the strong equalizing effect of changes in the education premium, pointing to an effect in line with results for the declining inequality over the 2000s in many Latin American countries (see e.g. Maurizio and Monsalvo 2020 and Zapata-Román 2020 for similar studies for Argentina and Chile). This indicates that the most conventional explanation of changes in earnings inequality based on the relative scarcity of skilled workers should not be understated. Changes in the returns to routine versus non-routine tasks additionally contributed to the decline in inequality if measured by O*NET, whereas the country-specific measure, which should better represent the task content of Ghanaian occupations, shows no significant effect in this first period (see Table 14).

During the second subperiod, in which inequality substantially increased, the education premium continued to be inequality-reducing, but with a much lower intensity. The rise in inequality can be entirely attributed to changes in the returns to routine versus non-routine tasks at the occupation level, if measured by the country-specific index. However, our results using the O*NET RTI measure do not confirm this effect, indicating again that the way RTI is measured matters. It is noteworthy that the changes in the returns to formality of workers played no relevant part in driving the inequality trend in either subperiod.

Table 14: RIF-regression decomposition of the change in earnings inequality (Gini index), 2005/06–16/17

	RTI (country-specific)			RTI (O*NET)		
	2005/06–12/13	2012/13–16/17	2005/06–16/17	2005/06–12/13	2012/13–16/17	2005/06–16/17
Change	−0.028	0.021	−0.007	−0.028	0.021	−0.007
	(0.009)	(0.006)	(0.009)	(0.009)	(0.006)	(0.009)
Reweighting						
Composition	0.004	−0.009	−0.007	0.007	−0.009	−0.006
	(0.004)	(0.002)	(0.004)	(0.005)	(0.002)	(0.005)
Earnings structure	−0.032	0.030	0.000	−0.035	0.030	−0.001
	(0.010)	(0.006)	(0.010)	(0.011)	(0.006)	(0.011)
RIF						
Composition	0.008	−0.009	−0.003	0.010	−0.009	−0.002
	(0.004)	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)
Specification error	−0.004	0.000	−0.004	−0.003	0.000	−0.004
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.003)
Earnings structure	−0.032	0.030	−0.001	−0.035	0.030	−0.001
	(0.010)	(0.006)	(0.010)	(0.010)	(0.006)	(0.011)

Reweighting error	0.000	0.000	0.000	−0.001	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)
Detailed composition						
Education	0.005	−0.005	−0.003	0.003	−0.005	−0.006
	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.003)
Formality	0.002	−0.004	−0.002	0.003	−0.005	−0.002
	(0.001)	(0.001)	0.001)	(0.001)	(0.001)	0.001)
Detailed structure						
Age	−0.002	−0.007	−0.006	0.004	−0.006	−0.001
	(0.007)	(0.005)	(0.008)	(0.008)	(0.005)	(0.009)
Gender	0.013	−0.005	0.006	0.012	0.006	0.015
	(0.010)	(0.007)	(0.011)	(0.011)	(0.007)	(0.011)
Education	−0.037	−0.007	−0.036	−0.029	−0.009	−0.030
	(0.012)	(0.011)	(0.014)	(0.012)	(0.011)	(0.014)
Ethnic	0.006	0.000	0.000	0.008	0.001	0.003
	(0.009)	(0.006)	(0.010)	(0.010)	(0.006)	(0.010)
RTI	−0.002	0.034	0.035	−0.016	−0.003	−0.021
	(0.017)	(0.012)	(0.015)	(0.014)	(0.004)	(0.017)
Formality	−0.002	0.008	0.006	0.000	0.007	0.010
	(0.007)	(0.006)	(0.008)	(0.007)	(0.006)	(0.008)
Intercept	−0.008	0.008	−0.005	−0.014	0.034	0.022
	(0.030)	(0.021)	(0.029)	(0.031)	(0.018)	(0.030)

Note: bootstrapped standard errors in parentheses (500 replications).

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

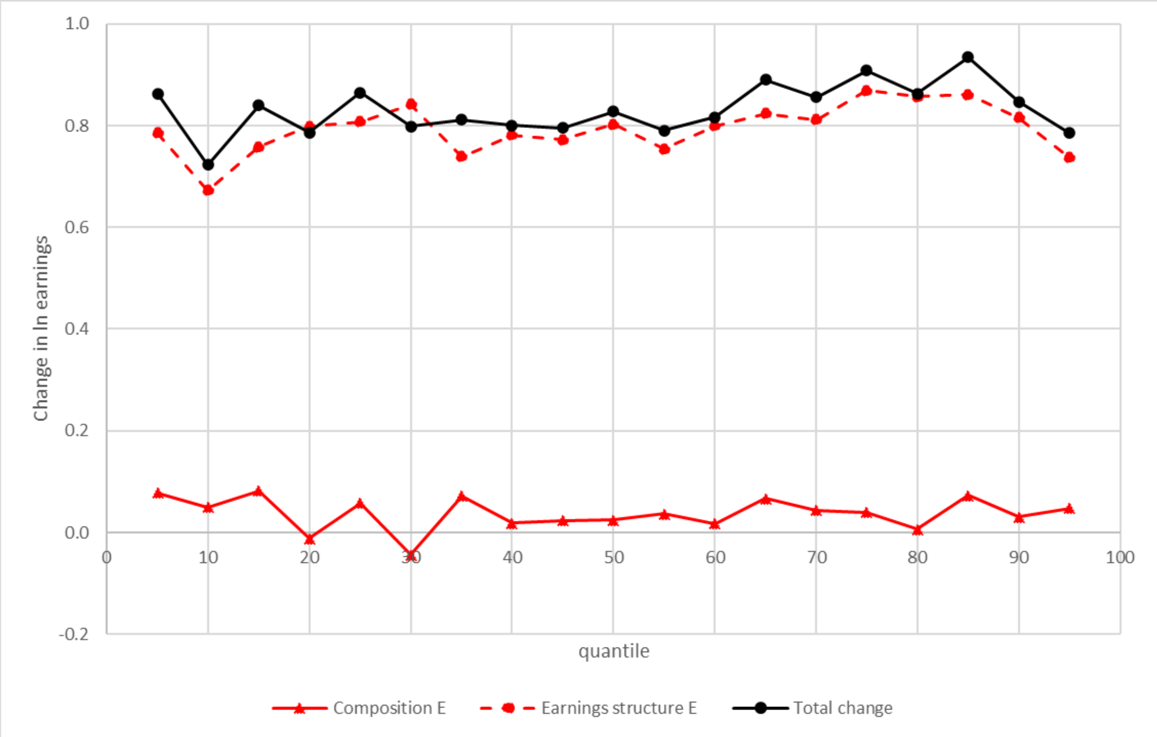
The concentration index presented in Section 4.2 tested for a monotonic relationship between earnings and RTI, pointing to a weaker relationship in the second subperiod of growing inequality. The regression-based decomposition presented here, apart from controlling for other characteristics, allows us to explore a more flexible non-monotonic relation between RTI and inequality (by including a quadratic term). Thereby, it captures the fact that the top-percentile occupations are not necessarily the least routine, and that this feature intensified over time, as previously discussed.

The Gini index summarizes the distributional changes along the entire distribution, reflecting the aggregate impact on inequality. However, it is important to disentangle how the different effects operate along the entire earnings distribution, as they are not necessarily uniform. For this purpose, we use the RIF-regression decomposition technique to decompose changes over time by (log) quantiles.

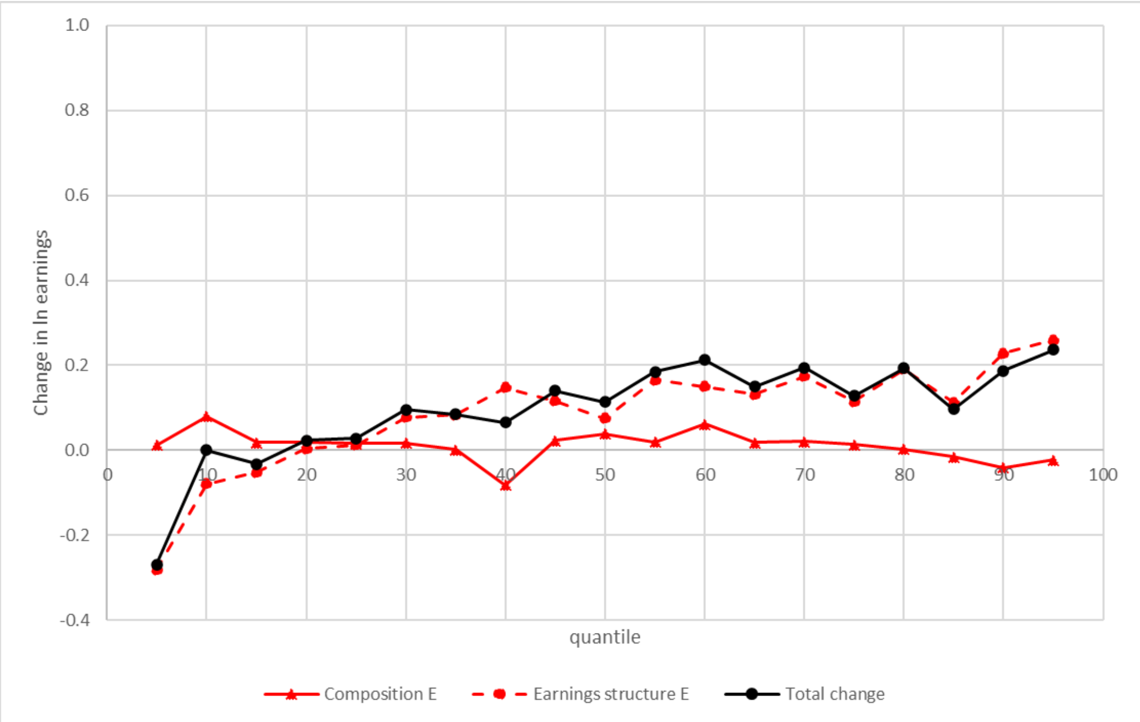
The aggregate decomposition of the change in earnings quantiles shows that the earnings structure effect drives the trend in both subperiods, over the entire distribution and not only at specific points (see Figure 8).

Figure 8: Reweighted RIF decomposition (country-specific RTI) of the change in earnings by quantile

(a) 2005/06–12/13



(b) 2012/13–16/17



Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

The detailed decomposition of the earnings structure effect clearly shows a kind of polarizing effect of the change in country-specific RTI occupation returns during the first subperiod, contributing to reducing earnings in the middle of the distribution while increasing earnings at the bottom and part of the top, that has no significant net effect on the Gini index, as seen above (see

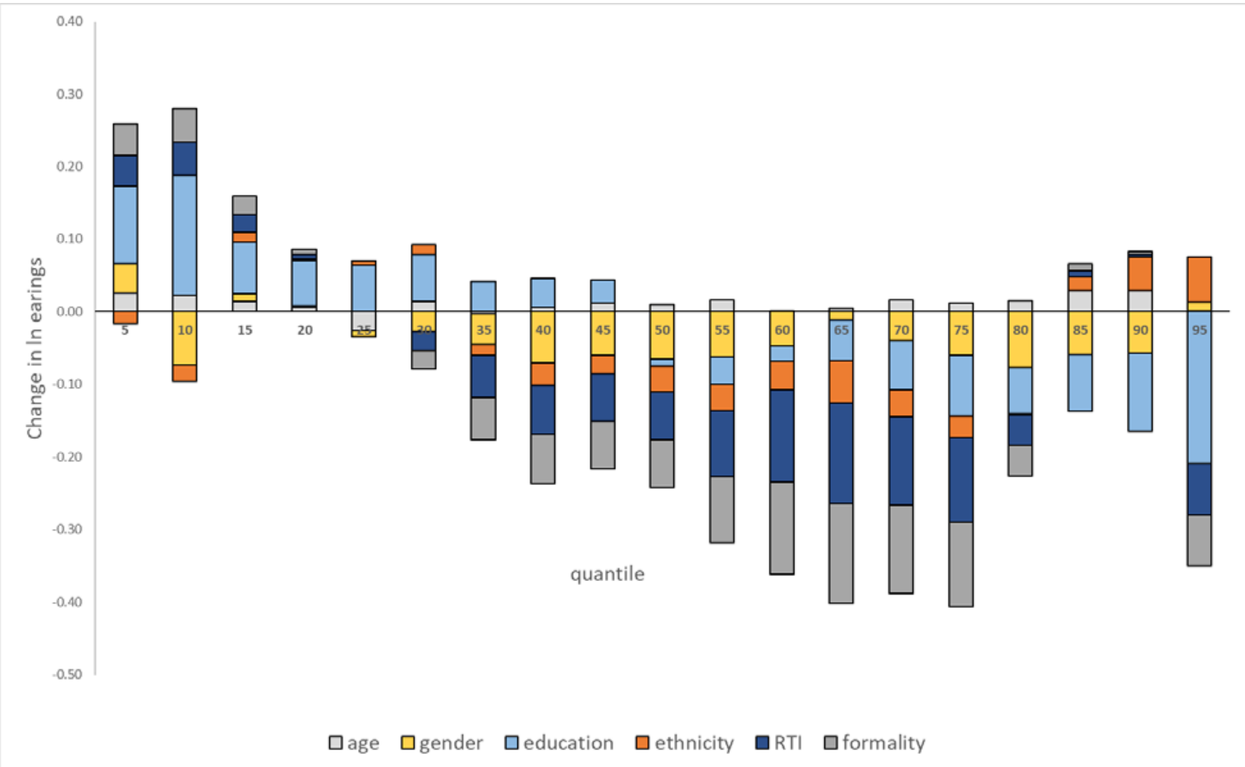
Figure 9). During the second period, the decomposition shows the clearly pro-rich profile of the change in the RTI effect on earnings quantiles, which explains the increase in Gini over these years, contributing to raise earnings above the 70th quantile and depressing them below the 60th.

With regard the changes in the returns to education, there is a clear pro-poor profile during the first period, raising earnings at the bottom and depressing them at the top, therefore contributing to reducing the Gini index. However, this pattern is less clear in the second period, when returns to education contributed to the decline in earnings both at the bottom and in the upper half of the distribution, with a more ambiguous effect on inequality.

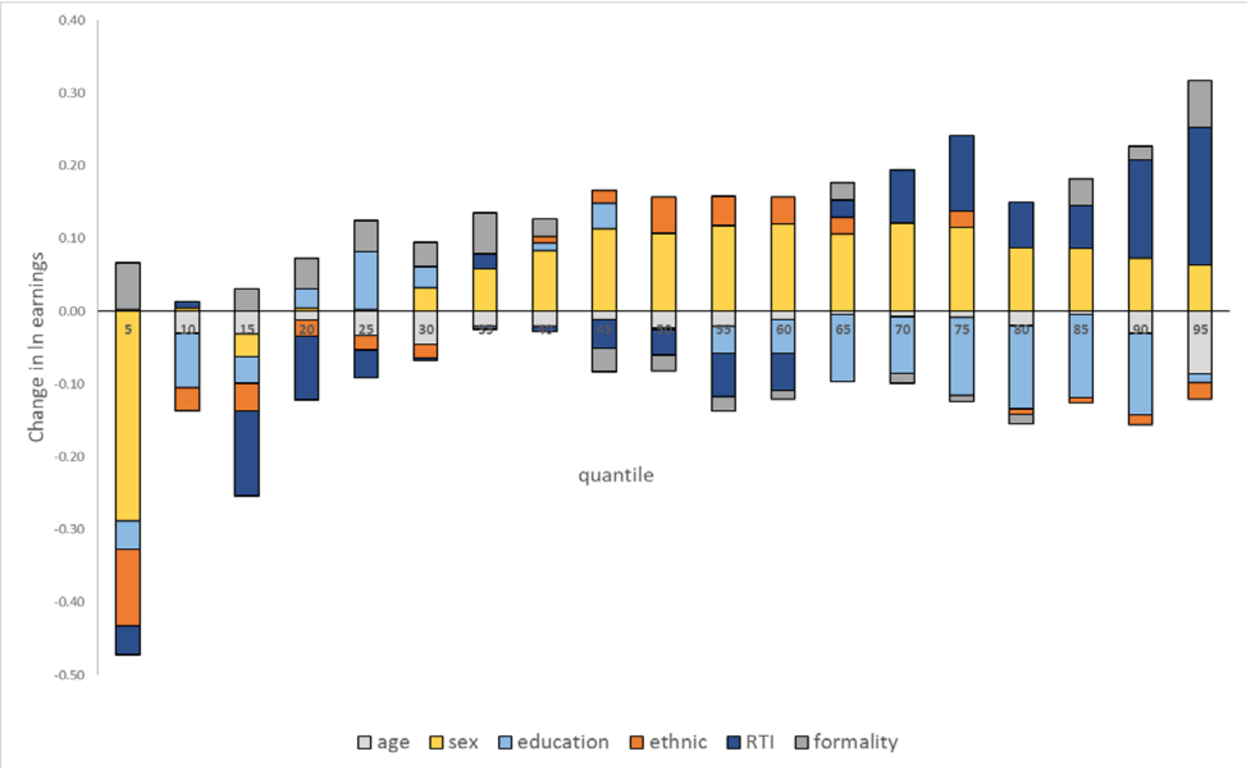
The changes in the returns to formality tended to increase the earnings at the very bottom of the distribution but decrease them everywhere else in the first period, and showed a slightly polarizing effect in the second period (increasing earnings at both extremes) but with no substantial effect on inequality overall. Running the RIF decomposition separately for formal and informal workers suggests that the role of the education premium in the first period and of the returns to RTI in the second period tends to be more intense among informal workers but applies to both groups. The null effect of returns to country-specific RTI in the first period is different, though, having an equalizing effect for informal workers and a disequalizing effect among formal workers.

Figure 9: Detailed RIF decomposition (country-specific RTI) of the earnings structure effect by quantile

(a) 2005/06–12/13



(b) 2012/13–16/17



Note: see also Table B8.

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

5 Conclusion

We find that the entire period from 2005/06 to 2016/17 was characterized by substantial structural changes in the composition of employment in Ghana, driven primarily by a sharp reduction in the relative share of employment in agriculture, most pronounced in the first subperiod up to 2012/13. As in other Sub-Saharan African countries, this shift was accompanied not by a rise in manufacturing employment but by an expansion of the service sector. These changes in the occupational structure imply a shift towards jobs demanding higher skills and involving less-routine tasks. The average RTI index declined, regardless of whether this is measured using the country-specific survey-based measure or the US O*NET expert-based measure.

Earnings inequality among paid employees and non-farm self-employed workers in Ghana, as measured by the Gini index, did not change much over the entire period (2005/06 to 2016/17) but showed striking differences by subperiod. We observe a substantial decline in inequality during the first subperiod (2005/06 to 2012/13), in which the economy grew much faster, with the largest earnings increases taking place at the bottom percentiles and the smallest growth being experienced at the top percentiles. This was followed by a second period (2012/13 to 2016/17) in which the economy kept growing, but at a slower pace and with a clear pro-rich pattern.

We have shown that the decline in inequality in the first period involved a depolarizing trend, with both employment and earnings growing more strongly in middle-earnings occupations. This reduction in inequality was the combined result of declining inequality within occupations and narrowing gaps in average earnings among occupations. In contrast, the rise in inequality in the second period was entirely driven by a surge in inequality within occupations, to a large extent driven by some occupations with growing employment becoming more unequal, while inequality between occupations kept declining. However, we did not find clear evidence that this increase in inequality was associated with polarization in average earnings or employment by occupation, in terms of either occupation average earnings or task content.

Our RIF decomposition results indicate that in both periods the trends in inequality are primarily explained by changes in the earnings structure, while the composition effect is small. This means that shifts in employment per se had no substantial impact on inequality unless they contributed to changes in the earnings structure. The decline in earnings inequality during the first subperiod, indeed, can be associated with a substantial decline in the education premium, following a general improvement in the level of education across the workforce. The rise in inequality that followed in the second subperiod was possible due to a combination of two effects. First, we observe a slow-down in the decline of the education premium—resulting in a smaller equalizing effect. Second, we find a disequalizing effect brought about by changes in the remuneration of non-routine jobs with high demand for cognitive analytical and interpersonal tasks, relative to more-routine occupations.

In summary, we found evidence suggesting that traditional factors related to the relative scarcity of skills are key to understanding the trend in inequality in Ghana. This highlights the importance of continuing the expansion of education to ensure that the supply of skills outpaces the expected increasing demand, to prevent inequality skyrocketing in an already highly unequal country. However, we have also shown that even in a period in which the education premium falls, inequality can increase as the result of changes in the way routine and non-routine tasks performed by workers are remunerated in the labour market, and there are reasons to believe that this may be accentuated in the future as the country catches up with more-advanced countries in incorporating technology. This happened in the context of a development process that, as in other Sub-Saharan countries that can learn from the Ghanaian experience, has implied little real structural transformation and then little exposure to the potential effects of automation and international trade. Even if the workforce is becoming more skilled and performing less-routine jobs, the persistently low productivity of newly created jobs, whether routine or not, can be highly disequalizing and needs to be addressed.

References

Acemoglu, D., and D.H. Autor (2011). 'Skills, Tasks and Technologies: Implications for Employment and Earnings'. In D. Card and O. Ashenfelter (eds), *Handbook of Labor Economics*. Amsterdam: Elsevier. https://doi.org/10.1016/S0169-7218(11)02410-5

Arias, O.S., C. Sánchez-Páramo, M.E. Dávalos, I. Santos, E.R. Tiongson, C. Gruen, N. de Andrade Falcão, G. Saiovici, and C.A. Cancho (2014). *Back to Work: Growing with Jobs in Europe and Central Asia Reports*. Washington, DC: World Bank. https://doi.org/10.1596/978-0-8213-9910-1

Aryeetey, E., and W. Baah-Boateng (2016). 'Understanding Ghana's Growth Success Story and Job Creation Challenges'. In H. Bhorat and F. Tarp (eds), *Understanding the African Lions: Growth Traps and Opportunities in Six Dominant African Economies*. Washington, DC: Brookings Institution Press.

Autor, D., and D. Dorn (2009). 'This Job is "Getting Old": Measuring Changes in Job Opportunities using Occupational Age Structure'. *American Economic Review: Papers and Proceedings*, 99(2): 45–51. https://doi.org/10.1257/aer.99.2.45

Autor, D., and D. Dorn (2013). 'The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market'. *American Economic Review*, 103(5): 1553–97. https://doi.org/10.1257/2020aer.103.5.1553

Autor, D.H., F. Levy, and R.J. Murnane (2003). 'The Skill Content of Recent Technological Change: An Empirical Exploration'. *The Quarterly Journal of Economics*, 118(4): 1279–333. https://doi.org/10.1162/003355303322552801

Baumgarten, D., I. Geishecker, and H. Görg (2013). 'Offshoring, Tasks, and the Skill-Wage Pattern'. *European Economic Review*, 61(C): 132–52. 10.1016/j.euroecorev.2013.03.007

Baymul, C., and K. Sen (2020). 'Was Kuznets Right? New Evidence on the Relationship between Structural Transformation and Inequality'. *The Journal of Development Studies*, special section: 'Double Dividends and Mixed Blessings: Structural Transformation, Income Inequality and Employment Dynamics': 1643–62. https://doi.org/10.1080/00220388.2019.1702161

Du Y., and A. Park (2018). 'Changing Demand for Tasks and Skills in China'. Background report for the World Bank Group (WBG)-Development Research Center (DRC) of the State Council of the People's Republic of China report on New Drivers of Growth in China. Washington, DC: WBG; Beijing: DRC.

Fernández-Macías, E., and J. Hurley (2017). 'Routine-Biased Technical Change and Job Polarization in Europe'. *Socio-Economic Review*, 15(3): 563–85. https://doi.org/10.1093/ser/mww016

Firpo, S., N.M. Fortin, and T. Lemieux (2007). 'Decomposing Wage Distributions using Recentered Influence Function Regressions'. Unpublished manuscript, Vancouver: University of British Columbia.

Firpo, S., N.M. Fortin, and T. Lemieux. (2009). 'Unconditional Quantile Regressions'. *Econometrica*, 77(3): 953–73. https://doi.org/10.3982/ECTA6822

Firpo, S., N.M. Fortin, and T. Lemieux (2011). 'Occupational Tasks and Changes in the Wage Structure'. IZA Discussion Paper 5542. Bonn: Institute of Labor Economics (IZA).

Firpo, S., N.M. Fortin, and T. Lemieux (2018). 'Decomposing Wage Distributions Using Recentered Influence Function Regressions'. *Econometrics*, 6(2): 1–40. https://doi.org/10.3390/econometrics6020028

Fortin, N.M., T. Lemieux, and S. Firpo (2011), 'Decomposition Methods in Economics'. In O. Ashenfelter and D. Card (eds), *Handbook of Labor Economics*. Amsterdam: North Holland. https://doi.org/10.1016/S0169-7218(11)00407-2

Goldin, C., and L.F. Katz (2010). *The Race between Education and Technology*. Cambridge, MA: The Belknap Press. https://doi.org/10.2307/j.ctvjf9x5x

Goos, M., and A. Manning (2007). 'Lousy and Lovely Jobs: The Rising Polarization of Work in Britain'. *The Review of Economics and Statistics*, 89(1): 118–33. https://doi.org/10.1162/rest.89.1.118

Goos, M., A. Manning, and A. Salomons (2014). 'Explaining Job Polarization: Routine-Biased Technological Change and Offshoring'. *American Economic Review*, 104: 2509–26. https://doi.org/10.1257/aer.104.8.2509

Gradín, C., M. Leibbrandt and F. Tarp (eds) (forthcoming). *Inequality in the Developing World*. New York: Oxford University Press.

Grossman, G.M., and E. Rossi-Hansberg (2008). 'Trading Tasks: A Simple Theory of Offshoring'. *American Economic Review*, 98(5): 1978–97. https://doi.org/10.1257/aer.98.5.1978

GSS (2008). 'Ghana Living Standard Survey V 2005–2006 (GLSS 5), v2.0'. Accra: Ghana Statistical Service (GSS). Available at: https://www2.statsghana.gov.gh/nada/index.php/catalog/5 (accessed 17 May 2019).

GSS (2014). 'Ghana Living Standards Survey VI 2012-2013 (GLSS 6), v1.0'. Accra: GSS. Available at: https://www2.statsghana.gov.gh/nada/index.php/catalog/72 (accessed 17 May 2019).

GSS (2018a). 'Ghana Living Standard Survey VII 2016-2017 (GLSS 7), v1.0'. Accra: GSS. Available at: https://www2.statsghana.gov.gh/nada/index.php/catalog/97 (accessed 17 May 2019).

GSS (2018b). 'Ghana Living Standards Survey Round 7 (GLSS 7): Poverty Trends in Ghana, 2005–2017'. Accra: GSS. Available at: www2.statsghana.gov.gh (accessed 8 January 2020).

Handel, M.J. (2012). 'Trends in Job Skill Demands in OECD Countries'. OECD Social, Employment and Migration Working Papers 143. Paris: OECD (Organisation for Economic Co-operation and Development).

Hardy, W., R. Keister, and P. Lewandowski (2016). 'Technology or Upskilling? Trends in the Task Composition of Jobs in Central and Eastern Europe'. IBS Working Paper 01/2016. Warsaw: Instytut Badań Strukturalnych (IBS).

Hardy, W., R. Keister, and P. Lewandowski. (2018a). 'Educational upgrading, structural change and the task composition of jobs in Europe'. *Economics of Transition*, 26 (2), 201–31. https://doi.org/10.1111/ecot.12145

Hardy, W., P. Lewandowski, A. Park, and D. Yang (2018b). 'The Global Distribution of Routine and Non-Routine Work: Findings from PIAAC, STEP and CULS'. IBS Working Paper 05/2018. Warsaw: IBS.

ILO (2009). *Key Indicators of the Labour Market*. Geneva: International Labour Organization (ILO).

ILO (2016). 'ISCO-08 Structure, Index Correspondence with ISCO-88'. Geneva: ILO. Available at: https://www.ilo.org/public/english/bureau/stat/isco/isco08/index.htm (accessed 16 March 2020).

ILO (2020). 'ILOSTAT database'. Geneva: ILO. Available at: https://ilostat.ilo.org/data (accessed 16 March 2020).

IMF (2012). 'Ghana: Poverty Reduction Strategy Paper'. IMF Country Report 12/203, Washington, DC: International Monetary Fund. https://doi.org/10.5089/9781475506594.002

Katz, L.F., and D.H. Autor (1999). 'Changes in the Wage Structure and Earnings Inequality'. In O. Ashenfelter and D. Card (eds), *Handbook of Labor Economics*. Amsterdam: Elsevier. https://doi.org/10.1016/S1573-4463(99)03007-2

Katz, L.F., and K.M. Murphy (1992). 'Changes in Relative Wages, 1963–1987: Supply and Demand Factors'. *The Quarterly Journal of Economics*, 107(1): 35–78. https://doi.org/10.2307/2118323

Lewandowski, P., A. Park, W. Hardy, and Y. Du (2019). 'Technology, Skills, and Globalization: Explaining International Differences in Routine and Nonroutine Work using Survey Data'. IBS Working Paper 04/2019. Warsaw: IBS.

Lo Bello, S., M.L. Sanchez Puerta, and H.J. Winkler (2019). 'From Ghana to America: The Skill Content of Jobs and Economic Development'. World Bank Policy Research Working Paper 8758. Washington, DC: World Bank. https://doi.org/10.1596/31354

Maurizio, R., and A.P. Monsalvo (2020). 'The Changing Nature of Work: Implications for Employment and Inequality in Argentina 2003–2019'. Working Paper, forthcoming. Helsinki: UNU-WIDER.

McKay, A., and E. Aryeetey (2004). 'Operationalizing Pro-Poor Growth: A Country Case Study on Ghana'. Working Paper 32889. Washington, DC: World Bank. Available at: http://documents.worldbank.org/curated/en/310521468249924654/Operationalizing-pro-poor-growth-a-country-case-study-on-Ghana (accessed 15 March 2020).

McKay, A., J. Pirttilä, and F. Tarp (2016). 'Ghana: Poverty Reduction over Thirty Years'. In C. Arndt, A. McKay, and F. Tarp (eds), *Growth and Poverty in Sub-Saharan Africa*. Oxford: Oxford University Press.

Mywage.org/Ghana (2020). 'National Minimum Wage'. Available at: https://mywage.org/ghana/salary/minimum-wages (accessed 16 March 2020).

Odusola, A., G.A. Cornia, H. Bhorat, and P. Conceição (eds) (2017). *Income Inequality Trends in Sub-Saharan Africa: Divergence, Determinants and Consequences*. New York: United Nations Development Programme (UNDP)..

O*NET (2003). 'O*NET 5.0 Database, September 2003 Release'. Washington, DC: US Department of Labor. Available at: https://www.onetcenter.org (accessed 3 July 2019).

Sebastián, R. (2018a). 'Explaining Job Polarisation in Spain from a Task Perspective'. *SERIEs*, 9: 215–48. https://doi.org/10.1007/s13209-018-0177-1

Sebastián, R. (2018b). 'Technological Change and Employment Polarisation'. Thesis dissertation. Salamanca: University of Salamanca.

Shorrocks, A.F. (2013). 'Decomposition Procedures for Distributional Analysis: A Unified Framework Based on the Shapley Value'. *Journal of Economic Inequality*, 11(1): 99–126. https://doi.org/10.1007/s10888-011-9214-z

Spitz-Oener, A. (2006). 'Technical Change, Job Tasks, and Rising Educational Demands: Looking Outside the Wage Structure'. *Journal of Labor Economics*, 24(2): 235–70. https://doi.org/10.1086/499972

World Bank (2019). 'World Development Indicators'. Washington, DC: World Bank. Available at: https://databank.worldbank.org/source/world-development-indicators# (accessed 8 January 2020).

Zapata-Román, G. (2020). 'The Changing Nature of Work: Labour Market Effects of Structural Transformation in Chile'. Working Paper (forthcoming). Helsinki: UNU-WIDER.

Appendix

A Corrections in the coding of occupations between O*NET and survey data

We matched the O*NET task content measures to the GLSS survey data at the occupational level, using ISCO-88 occupational units at the three-digit level. In doing so, we encountered three major issues that were resolved as follows.

First, the non-routine cognitive task content in several agricultural occupations in ISCO-88 (611, 612, 613) is implausibly high, which translates into an implausibly low aggregate RTI in these occupations (considering that agriculture is typically associated with routine and manual tasks). This problem is not present if the revised ISCO-08 classification is merged with O*NET. Assuming a higher precision of the more recent classifications, we therefore decided to replace the values calculated using ISCO-88 by those obtained using ISCO-08 for the three affected occupational groups (Hardy et al. 2016).

Second, the ILO conversion table maps occupation code 5221(shop keepers) in ISCO-08 to 1314 (general managers in wholesale and retail trade) in ISCO-88, leading to inconsistencies in the RTI time-series between GLSS 5 and later survey waves. Diverging from this standard, occupations 5221 (shop keepers), 5222 (shop supervisors), and 5223 (shop sales assistants) are all mapped to occupational group 522 (shop salespersons) in ISCO-88 (Hardy et al. 2016). In addition, occupation 523 (stall and market salespersons), which is implausibly non-routine in ISCO-88, is recoded to 522 to ensure consistency.

Third, there are some ICSO-88 occupations that cannot be matched to occupational codes in O*NET. In these cases, where possible, we imputed the values of task items from the nearest matching occupational code. In particular:

- ISCO-88 0110 (armed forces) cannot be imputed and is dropped from the analysis
- ISCO-88 1110 (legislators) is assigned the task values of ISCO-88 1120 (senior government officials)
- ISCO-88 3240 (traditional medicine practitioners and faith healers) cannot be imputed and is dropped from the analysis
- ISCO-88 3340 (other teaching associate professionals) is assigned the average task values of ISCO-88 3310, 3320, and 3330 (primary, pre-primary, and special education teaching associate professionals)
- ISCO-88 9120 (shoe cleaning and other street services elementary occupations) is assigned the average task values of ISCO-88 9131, 9132, and 9133 (domestic and related helpers, cleaners, and launderers)

B Check for consistency of results when disaggregating occupations by workers' formality status

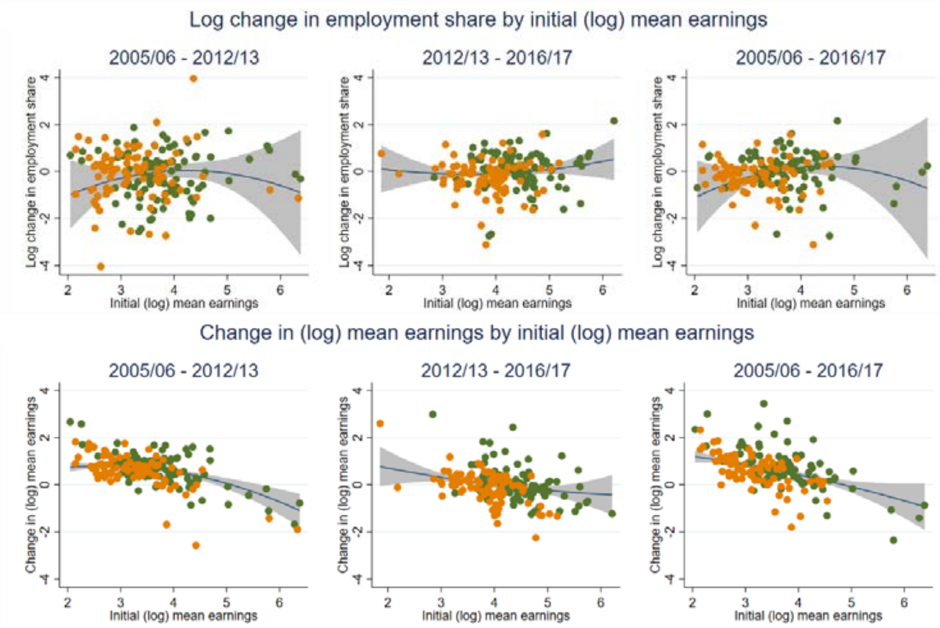
Table B1: Correlation between initial (log) earnings and changes in average employment and earnings by occupation (formal vs informal, three digits), 2005/06–16/17

	Log change in employment share			Change in log mean earnings		
	2005/06–12/13	2012/13–16/17	2005/06–16/17	2005/06–12/13	2012/13–16/17	2005/06–16/17
Formal workers						
(log) mean weekly earnings (t−1)	2.105	−2.689*	0.401	0.922*	−0.906	−1.776**
	(1.809)	(1.535)	(1.621)	(0.535)	(1.668)	(0.861)
Sq. (log) mean weekly earnings (t−1)	−0.194	0.278	−0.009	−0.155**	0.061	0.142
	(0.211)	(0.169)	(0.194)	(0.066)	(0.189)	(0.105)
Constant	−5.397	6.557*	−1.382	−0.588	2.767	5.237***
	(3.824)	(3.472)	(3.376)	(1.073)	(3.652)	(1.747)
Observations	93	88	88	93	88	88
Adj. R-squared	0.109	0.061	0.017	0.137	0.134	0.381
Informal workers						
(log) mean weekly earnings (t−1)	4.762***	−0.375	6.779*	0.796	0.038	−0.766
	(1.785)	(1.737)	(3.793)	(0.552)	(1.621)	(1.182)
Sq. (log) mean weekly earnings (t−1)	−0.617***	0.032	−0.984*	−0.171**	−0.057	0.036
	(0.229)	(0.239)	(0.571)	(0.083)	(0.218)	(0.184)
Constant	−8.731**	0.768	−11.524*	−0.095	0.715	2.745
	(3.425)	(3.134)	(6.299)	(0.901)	(2.986)	(1.857)
Observations	85	81	77	85	81	77
Adj. R-squared	0.099	−0.011	0.076	0.152	0.202	0.240

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

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

Figure B1: Correlation between initial (log) earnings and changes in average employment and earnings by occupation (formal vs informal, three digits), 2005/06–16/17



Note: scatter plot with fitted quadratic prediction and 95% confidence interval; yellow = informal, dark green = formal.

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

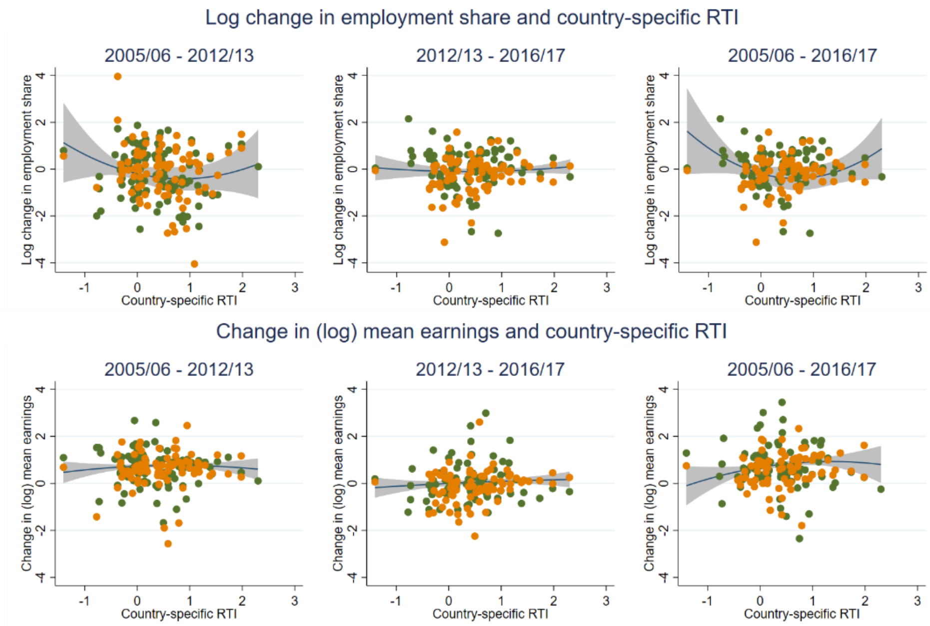
Table B2: Correlation between country-specific RTI and changes in average employment and earnings by occupation (formal vs informal, three digits), 2005/06–16/17

	Log change in employment share			Change in log mean earnings		
	2005/06–12/13	2012/13–16/17	2005/06–16/17	2005/06–12/13	2012/13–16/17	2005/06–16/17
Formal workers						
(log) mean weekly earnings (t−1)	−0.583**	0.064	−0.504**	−0.114	0.193	0.299
	(0.288)	(0.101)	(0.241)	(0.095)	(0.155)	(0.212)
Sq. (log) mean weekly earnings (t−1)	0.225	0.033	0.296**	0.047	−0.103	−0.109
	(0.174)	(0.069)	(0.148)	(0.080)	(0.103)	(0.176)
Constant	−0.242*	0.135*	0.009	0.722***	−0.023	0.656***
	(0.141)	(0.070)	(0.128)	(0.058)	(0.062)	(0.073)
Observations	93	88	88	93	88	88
Adj. R-squared	0.062	−0.007	0.040	−0.005	0.020	0.036
Informal workers						
(log) mean weekly earnings (t−1)	−0.590	0.159	−0.532	0.285*	−0.011	0.388*
	(0.572)	(0.172)	(0.592)	(0.148)	(0.105)	(0.207)
Sq. (log) mean weekly earnings (t−1)	0.377	−0.003	0.525	−0.184	0.055	−0.156
	(0.431)	(0.083)	(0.428)	(0.113)	(0.060)	(0.156)
Constant	−0.145	−0.294**	−0.375	0.695***	0.043	0.702***
	(0.251)	(0.112)	(0.272)	(0.060)	(0.071)	(0.102)
Observations	85	81	77	85	81	77
Adj. R-squared	−0.008	0.011	0.005	0.044	−0.009	0.052

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

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

Figure B2: Correlation between country-specific RTI and changes in average employment and earnings by occupation (formal vs informal, three digits), 2005/06–16/17



Note: scatter plot with fitted quadratic prediction and 95% confidence interval; yellow = informal, dark green = formal.

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

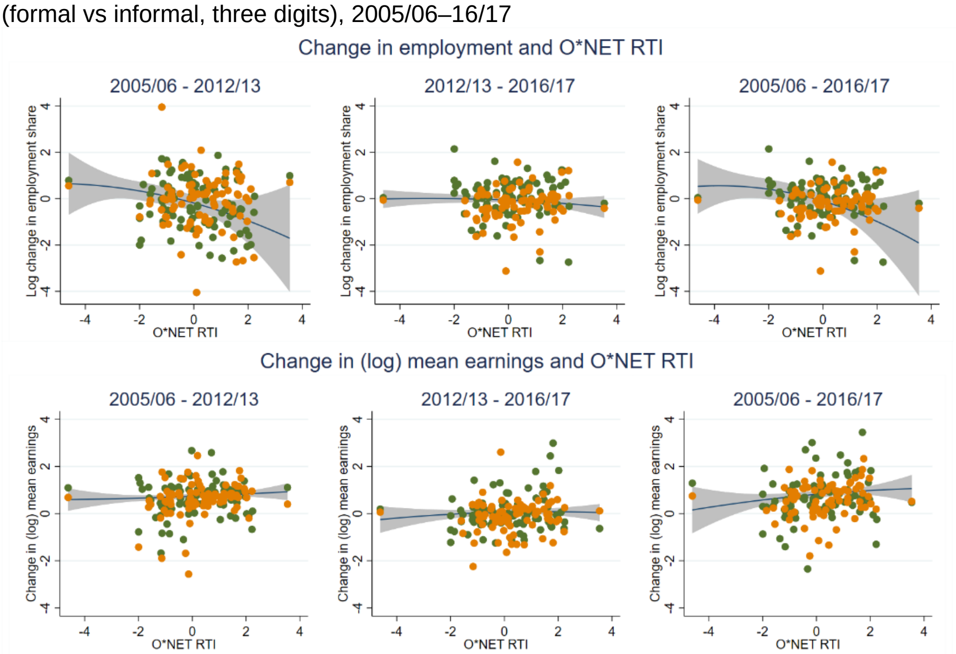
Table B3: Correlation between O*NET RTI and changes in average employment and earnings by occupation (formal vs. informal, three digits), 2005/06–16/17

	Log change in employment share			Change in log mean earnings		
	2005/06–12/13	2012/13–16/17	2005/06–16/17	2005/06–12/13	2012/13–16/17	2005/06–16/17
Formal workers						
(log) mean weekly earnings (t−1)	−0.371**	−0.028	−0.309***	0.046	0.061	0.168**
	(0.144)	(0.032)	(0.106)	(0.037)	(0.054)	(0.073)
Sq. (log) mean weekly earnings (t−1)	−0.019	−0.011	−0.018	0.027**	−0.005	0.026
	(0.051)	(0.011)	(0.040)	(0.012)	(0.026)	(0.037)
Constant	−0.375***	0.181**	−0.053	0.662***	0.017	0.712***
	(0.102)	(0.073)	(0.103)	(0.039)	(0.067)	(0.091)
Observations	93	88	88	93	88	88
Adj. R-squared	0.195	−0.017	0.155	0.010	0.009	0.092
Informal workers						
(log) mean weekly earnings (t−1)	−0.339	0.013	−0.329	0.045	−0.011	0.045
	(0.248)	(0.065)	(0.251)	(0.034)	(0.047)	(0.055)
Sq. (log) mean weekly earnings (t−1)	−0.032	−0.021	−0.065	−0.009	−0.003	−0.015
	(0.071)	(0.021)	(0.068)	(0.015)	(0.011)	(0.021)
Constant	−0.102	−0.158**	−0.131	0.761***	0.088	0.879***
	(0.220)	(0.072)	(0.222)	(0.056)	(0.066)	(0.087)
Observations	85	81	77	85	81	77
Adj. R-squared	0.063	−0.014	0.091	−0.003	−0.024	−0.014

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

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

Figure B3: Correlation between O*NET RTI and changes in average employment and earnings by occupation (formal vs informal, three digits), 2005/06–16/17



Note: scatter plot with fitted quadratic prediction and 95% confidence interval; yellow = informal, dark green = formal.

Source: authors' calculation based on GLSS 5, GLSS 6, and GLSS 7.

Table B4: Gini index decomposed into inequality between and within occupations (formal vs informal, two digits), 2005/06–16/17

	Actual			Shares constant			Means constant		
	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17
1 Overall Gini	0.571	0.544	0.566	0.571	0.544	0.568	0.571	0.566	0.587
Shapley decomposition									
2 Between-occupation	0.133	0.107	0.083	0.133	0.107	0.084	0.133	0.146	0.148
% ratio	23%	20%	15%	23%	20%	15%	23%	26%	25%
3 Within-occupation	0.438	0.436	0.483	0.438	0.436	0.484	0.438	0.420	0.438
% ratio	77%	80%	85%	77%	80%	85%	77%	74%	75%

Note: ISCO-88, two digits (distinguishing formal and informal workers in each occupation as different categories).

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

Table B5: Gini index decomposed into inequality between and within occupations (formal vs informal, three digits), 2005/06–16/17

	Actual			Shares constant			Means constant		
	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17	2005/06	2012/13	2016/17
1 Overall Gini	0.571	0.544	0.566	0.571	0.544	0.568	0.571	0.566	0.587
Shapley decomposition									
2 Between-occupation	0.155	0.129	0.128	0.133	0.107	0.129	0.155	0.165	0.183
% ratio	27%	24%	23%	23%	20%	23%	27%	29%	31%
3 Within-occupation	0.416	0.415	0.438	0.438	0.436	0.439	0.416	0.401	0.404
% ratio	73%	76%	77%	77%	80%	77%	73%	71%	69%

Note: ISCO-88, three digits (distinguishing formal and informal workers in each occupation as different categories).

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

Table B6: Change in the Gini index decomposed into the contribution of changes in employment shares (formal vs informal, two digits) and in mean earnings (Shapley decomposition based on Table B4), 2005/06–16/17

	2005/06–12/13	2012/13–16/17	2005/06–16/17
Change in employment shares (mean earnings constant)	0.006	0.020	0.026
Change in mean earnings (employment shares constant)	−0.032	−0.045	−0.077
Total change	−0.026	−0.025	0.051

Note: ISCO-88, three digits (distinguishing formal and informal workers in each occupation as different categories).

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

Table B7: Change in the Gini index decomposed into the contribution of changes in employment shares (formal vs informal, three digits) and in mean earnings (Shapley decomposition based on Table B5), 2005/06–16/17

	2005/06–12/13	2012/13–16/17	2005/06–16/17
Change in employment shares (mean earnings constant)	0.015	0.026	0.041
Change in mean earnings (employment shares constant)	−0.042	−0.027	−0.069
Total change	−0.027	−0.001	−0.028

Note: ISCO-88, three digits (distinguishing formal and informal workers in each occupation as different categories).

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

Table B7: RIF regressions of Gini index

	Country-specific						O*NET					
	2005/06		2012/13		2016/17		2005/06		2012/13		2016/17	
	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Age: 25–44	0.029	0.016	0.029	0.018	0.051	0.013	0.028	0.017	0.028	0.018	0.056	0.013
Age: 45–64	0.024	0.021	0.024	0.020	0.015	0.011	0.021	0.021	0.021	0.021	0.015	0.011
Female	0.046	0.018	0.046	0.018	0.063	0.010	0.050	0.020	0.050	0.020	0.061	0.010
No education	0.071	0.022	0.071	0.022	0.023	0.012	0.077	0.022	0.077	0.022	0.032	0.012
Preschool	0.032	0.021	0.032	0.020	0.021	0.015	0.040	0.021	0.040	0.021	0.031	0.015
Primary	0.041	0.021	0.041	0.021	0.021	0.016	0.044	0.021	0.044	0.022	0.028	0.016
Upper-secondary	0.018	0.032	0.018	0.035	−0.008	0.014	0.000	0.031	0.000	0.033	−0.015	0.014
Post-secondary	−0.048	0.024	−0.048	0.023	−0.088	0.017	−0.073	0.026	−0.073	0.025	−0.097	0.017
Tertiary	0.271	0.074	0.271	0.073	0.000	0.023	0.231	0.078	0.231	0.077	−0.011	0.022
Mole-Dagbon	0.080	0.034	0.080	0.034	0.008	0.012	0.077	0.034	0.077	0.034	0.009	0.012
Ewe	−0.050	0.017	−0.050	0.016	0.007	0.011	−0.051	0.017	−0.051	0.016	0.005	0.011
Ga-Dangme	−0.044	0.018	−0.044	0.018	−0.006	0.014	−0.044	0.018	−0.044	0.018	−0.008	0.014
Gurma	0.015	0.043	0.015	0.045	0.036	0.032	0.014	0.043	0.014	0.044	0.034	0.032
Guan	−0.060	0.019	−0.060	0.021	0.019	0.024	−0.059	0.019	−0.059	0.020	0.019	0.024
Grusi	−0.011	0.062	−0.011	0.058	−0.071	0.020	−0.011	0.062	−0.011	0.058	−0.071	0.021
Mande	−0.053	0.032	−0.053	0.033	−0.007	0.038	−0.058	0.032	−0.058	0.034	−0.008	0.037
Other groups	−0.056	0.040	−0.056	0.041	−0.027	0.022	−0.061	0.040	−0.061	0.040	−0.029	0.022
RTI	−0.013	0.063	−0.013	0.064	−0.053	0.029	−0.023	0.018	−0.023	0.018	−0.018	0.006
RTI square	0.050	0.043	0.050	0.044	0.074	0.021	0.002	0.014	0.002	0.013	−0.008	0.004
Formality	−0.048	0.020	−0.048	0.019	−0.052	0.012	−0.061	0.021	−0.061	0.019	−0.062	0.012
Intercept	0.502	0.027	0.502	0.028	0.499	0.015	0.541	0.027	0.541	0.027	0.527	0.013
Observations	5,344		10,243		7,926		5,344		10,243		7,926	

Note: bootstrapped standard errors (500 replications).

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.

Table B8: RIF-regression decomposition of the change in earnings quantiles (country-specific RTI)

(a) 2005/06–12/13

	Quantile																		
	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95
Final	2.06	2.38	2.78	2.97	3.16	3.33	3.47	3.66	3.75	3.91	4.01	4.15	4.35	4.47	4.67	4.83	5.05	5.26	5.64
	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)
Initial	1.19	1.66	1.94	2.19	2.30	2.53	2.65	2.86	2.96	3.08	3.22	3.33	3.46	3.61	3.77	3.96	4.12	4.41	4.86
	(0.07)	(0.04)	(0.04)	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.05)
Change	0.86	0.72	0.84	0.79	0.87	0.80	0.81	0.80	0.80	0.83	0.79	0.82	0.89	0.86	0.91	0.86	0.93	0.85	0.79
	(0.08)	(0.06)	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)	(0.03)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.06)
Reweighting																			
Composition	0.08	0.05	0.08	-0.01	0.06	-0.04	0.07	0.02	0.02	0.03	0.04	0.02	0.07	0.04	0.04	0.01	0.07	0.03	0.05
	(0.05)	(0.04)	(0.04)	(0.02)	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)
Earnings Structure	0.79	0.67	0.76	0.80	0.81	0.84	0.74	0.78	0.77	0.80	0.75	0.80	0.82	0.81	0.87	0.86	0.86	0.82	0.74
	(0.05)	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)
Total	0.86	0.72	0.84	0.79	0.87	0.80	0.81	0.80	0.80	0.83	0.79	0.82	0.89	0.86	0.91	0.86	0.93	0.85	0.79
	(0.10)	(0.09)	(0.09)	(0.05)	(0.07)	(0.08)	(0.08)	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)	(0.09)
RIF																			
Composition	0.03	0.04	0.03	0.02	0.03	0.03	0.02	0.02	0.03	0.03	0.02	0.02	0.03	0.04	0.05	0.05	0.06	0.06	0.07
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Specification Error	0.04	0.01	0.06	-0.03	0.03	-0.07	0.05	0.00	0.00	0.00	0.01	-0.01	0.04	0.00	-0.01	-0.05	0.02	-0.03	-0.03
	(0.04)	(0.04)	(0.03)	(0.02)	(0.02)	(0.04)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)
Earnings Structure	0.79	0.68	0.76	0.80	0.81	0.85	0.74	0.78	0.77	0.81	0.76	0.80	0.83	0.82	0.87	0.86	0.87	0.82	0.74
	(0.05)	(0.05)	(0.05)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)

Reweighting Error	-0.01	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Detailed structure																			
Age	0.03	0.02	0.01	0.01	-0.03	0.01	0.00	0.01	0.01	0.01	0.02	0.00	0.00	0.02	0.01	0.01	0.03	0.03	0.00
	(0.04)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
Gender	0.04	-0.07	0.01	0.00	-0.01	-0.03	-0.04	-0.07	-0.06	-0.07	-0.06	-0.05	-0.01	-0.04	-0.06	-0.08	-0.06	-0.06	0.01
	(0.05)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.06)
Education	0.11	0.17	0.07	0.06	0.06	0.06	0.04	0.04	0.03	-0.01	-0.04	-0.02	-0.06	-0.07	-0.08	-0.06	-0.08	-0.11	-0.21
	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.08)
Ethnic	-0.02	-0.02	0.01	0.00	0.00	0.01	-0.02	-0.03	-0.02	-0.04	-0.04	-0.04	-0.06	-0.04	-0.03	0.00	0.02	0.05	0.06
	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.06)
RTI	0.04	0.05	0.02	0.01	0.00	-0.03	-0.06	-0.07	-0.07	-0.07	-0.09	-0.13	-0.14	-0.12	-0.12	-0.04	0.01	0.00	-0.07
	(0.06)	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.10)
Formality	0.04	0.05	0.02	0.01	0.00	-0.03	-0.06	-0.07	-0.07	-0.07	-0.09	-0.13	-0.14	-0.12	-0.12	-0.04	0.01	0.00	-0.07
	(0.06)	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.07)	(0.10)
Intercept	0.61	0.53	0.64	0.74	0.80	0.85	0.86	0.95	0.90	1.00	1.00	1.06	1.12	1.09	1.17	1.04	0.97	0.91	0.97
	(0.10)	(0.11)	(0.08)	(0.07)	(0.08)	(0.09)	(0.08)	(0.08)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)	(0.09)	(0.10)	(0.10)	(0.11)	(0.11)	(0.18)

(b) 2012/13–16/17

	Quantile																		
	5	10	15	20	25	30	35	40	45	50	55	60	65	70	75	80	85	90	95
Final	1.79	2.38	2.75	3.00	3.19	3.43	3.55	3.72	3.89	4.02	4.20	4.36	4.50	4.67	4.80	5.02	5.15	5.45	5.88
	(0.06)	(0.03)	(0.02)	(0.03)	(0.04)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.05)
Initial	2.06	2.38	2.78	2.97	3.16	3.33	3.47	3.66	3.75	3.91	4.01	4.15	4.35	4.47	4.67	4.83	5.05	5.26	5.64
	(0.03)	(0.04)	(0.02)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.02)	(0.03)	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Change	-0.27	0.00	-0.03	0.02	0.03	0.09	0.08	0.07	0.14	0.11	0.18	0.21	0.15	0.19	0.13	0.19	0.10	0.19	0.24
	(0.07)	(0.05)	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)	(0.04)	(0.05)	(0.05)	(0.03)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.06)
Reweighting																			
Composition	0.02	0.10	0.04	-0.05	0.04	0.04	0.07	0.00	0.06	0.08	0.05	0.10	0.03	0.04	0.03	0.02	-0.01	-0.02	-0.02
	(0.01)	(0.03)	(0.03)	(0.05)	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)
Earnings Structure	-0.29	-0.10	-0.07	0.08	-0.01	0.06	0.01	0.06	0.08	0.03	0.13	0.12	0.12	0.15	0.10	0.17	0.10	0.21	0.26
	(0.07)	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)	(0.05)
Total	-0.27	0.00	-0.03	0.02	0.03	0.09	0.08	0.07	0.14	0.11	0.18	0.21	0.15	0.19	0.13	0.19	0.10	0.19	0.24
	(0.08)	(0.07)	(0.06)	(0.10)	(0.07)	(0.08)	(0.08)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)	(0.08)	(0.07)
RIF																			
Composition	0.03	0.05	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.04	0.01	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Specification Error	0.00	0.05	0.00	-0.09	0.00	0.00	0.03	-0.05	0.01	0.03	0.00	0.05	-0.01	-0.01	-0.02	-0.02	-0.02	-0.02	-0.01
	(0.01)	(0.03)	(0.03)	(0.05)	(0.02)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)
Earnings Structure	-0.29	-0.10	-0.07	0.08	-0.01	0.06	0.01	0.06	0.08	0.03	0.14	0.12	0.12	0.15	0.10	0.17	0.11	0.21	0.26
	(0.07)	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)	(0.05)
Reweighting Error	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Detailed structure																			
Age	0.00	-0.03	-0.03	-0.01	-0.03	-0.05	-0.02	-0.02	-0.01	-0.02	-0.02	-0.01	0.00	-0.01	-0.01	-0.02	0.00	-0.03	-0.09
	(0.04	(0.03	(0.03	(0.03	(0.02	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.04)
Gender	-0.29	0.00	-0.03	0.00	0.00	0.03	0.06	0.08	0.11	0.11	0.12	0.12	0.11	0.12	0.12	0.09	0.09	0.07	0.06
	(0.06	(0.05	(0.04	(0.04	(0.04	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.06)
Education	-0.04	-0.07	-0.04	0.03	0.08	0.03	0.00	0.01	0.04	0.00	-0.04	-0.05	-0.09	-0.08	-0.11	-0.11	-0.11	-0.11	-0.01
	(0.08	(0.06	(0.05	(0.05	(0.05	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.08)
Ethnic	-0.10	-0.03	-0.04	-0.02	-0.02	-0.02	0.00	0.01	0.02	0.05	0.04	0.04	0.02	0.00	0.02	-0.01	-0.01	-0.01	-0.02
	(0.05	(0.04	(0.03	(0.03	(0.03	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.05)
RTI	-0.04	0.01	-0.12	-0.09	-0.04	0.00	0.02	-0.01	-0.04	-0.04	-0.06	-0.05	0.02	0.07	0.10	0.06	0.06	0.14	0.19
	(0.07	(0.06	(0.06	(0.05	(0.05	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.09)
Formality	-0.04	0.01	-0.12	-0.09	-0.04	0.00	0.02	-0.01	-0.04	-0.04	-0.06	-0.05	0.02	0.07	0.10	0.06	0.06	0.14	0.19
	(0.07	(0.06	(0.06	(0.05	(0.05	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.07)	(0.09)
Intercept	0.11	0.02	0.15	0.13	-0.04	0.03	-0.10	-0.03	0.00	-0.04	0.11	0.08	0.04	0.06	-0.02	0.18	0.05	0.14	0.06
	(0.14	(0.10	(0.08	(0.08	(0.09	(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.08)	(0.09)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.11)	(0.14)

Note: bootstrapped standard errors in parentheses (500 replications).

Source: authors' calculations based on GLSS 5, GLSS 6, and GLSS 7.