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Evolution of wage inequality in India (1983–2017)

The role of occupational task content

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Abstract: We examine data for urban workers in the non-agricultural sector across three decades, 1983–2017, and find that earnings inequality increased during 1983–2004, was largely stable during 2004–11, and decreased during 2011–17. We explore whether decline in routine jobs and change in demand for skills has shaped evolution of earnings inequality in India. We rule out earnings polarization as an explanation for rising earnings inequality during 1983–2004, and then use Shapley and recentred influence functions (RIF) decomposition methods to decompose the change in Gini into the contribution from change in worker demographics and routine task intensity and the accompanying changes in returns to these characteristics. Our results show that changes in returns to education and routine task intensity explain a small part of the trends in wage inequality. Hence, in the Indian context, institutional factors may have played a bigger role in shaping wage inequality.

Key words: skills, tasks, earnings inequality, decomposition, India

JEL classification: D63, J21, J24

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1 Introduction

Changing technologies at work are transforming the labour market. Existing evidence shows that high-skilled workers are more likely to benefit from these changes than low-skilled workers. In this context, two phenomena in developed countries have received a lot of attention lately: the rising wage inequality in the USA and the UK due to a fall in real wages of less educated workers (Acemoglu and Autor 2011; Autor 2019; Blundell et al. 2018; Firpo et al. 2011); and the increasing job and earnings polarization over time (Acemoglu and Autor 2011; Goos and Manning 2007; Goos et al. 2009).[1] The U-shaped relationship between employment changes and skill content of jobs characterizes the increasing job polarization. This U-shape has been attributed to a rise in demand for managerial, professional, and technical jobs, along with a reduction in clerical jobs that are routine in nature and hence amenable to automation or outsourcing. At the lowest end of the skill spectrum, low-skill jobs that include manual work requiring physical strength have also seen an increase. This U-shaped pattern in employment change has been concomitant with polarization in earnings across skills, with a larger increase in wages for low- and high-skilled workers as demand for them has increased at a faster pace. The polarization of jobs has also pushed workers in the middle of the skill distribution towards the lower-skilled jobs, thus increasing inequality in the earnings distribution over time.

Discussion of job polarization in developed countries is incomplete without a simultaneous understanding of what is happening in developing countries, as job polarization is often based on use of machines and increased outsourcing from developed to developing countries (Goos et al. 2014). This has meant either a complete erasure of middle-skill jobs or a transfer of middle-skill jobs to developing countries. What is not well understood is how jobs are changing within developing countries. Is it indeed the case that middle-skill jobs are being wiped out across the globe due to technological changes, or is it that they are simply being transferred from developed to developing countries? The answer to this question depends on many factors other than offshoring to developing countries. First, it depends on where the routine jobs are situated—at the low, middle, or high end of the wage distribution—which itself can vary across developed and developing countries. Second is the degree of technological change in the country, third is the export structure of the country, and fourth is institutional factors like minimum wage changes and changes in demand and supply of labour at different skills levels. These factors may affect earnings inequality in the country. This paper aims to shed some light on this question as existing studies for developing countries look at job polarization or earnings inequality in isolation. A few studies examine the phenomenon of job polarization in developing countries. These include studies on India (Vashisht and Dubey 2019), Ukraine (Kupets 2016), and Mexico (Medina and Posso 2010).

In this paper, we look at changes in earnings inequality and in skill content of jobs for India, a developing country. The evolution of earnings inequality in India has been examined by Kijima (2006) and Chamarbagwala (2006), and later by Azam (2012). A study by Sarkar (2019) looks at changes in earnings inequality under the lens of a changing occupational structure in India up to 2011. She concludes that earnings inequality has been increasing in India and, to some extent, this can be explained by employment and wage polarization in the country. However, none of these studies examine changes in wage earnings inequality and its determinants post-2011 for India. The Indian economy has been undergoing rapid structural changes since 2004, with the service sector at the forefront of the high economic growth witnessed during 2004–12. Service sector exports have contributed the most to rising exports and India now dominates world exports in telecommunications and information technology (IT) services.[2] Services exports in India amounted to a meagre US$8.9 billion in 1997, but had risen to US$205.11

[1] Job polarization refers to a rise in employment share of low- and high-level jobs, alongside a fall in the share of mid-level jobs (when jobs are arranged along increasing wage or skill distributions).

[2] See www.thedollarbusiness.com/magazine/services-exportspotential-unleashed-or-an-unfinished-agenda/45913.

billion by 2018. The sector that has contributed most to the structural transformation from agriculture to non-agriculture has been construction, which has witnessed a large increase in employment growth since 2004. Therefore, a notable feature of economic growth in India has been service sector-led growth in the trade sector and construction-led growth domestically rather than manufacturing-led growth, unlike China and other South East Asian countries. Therefore, we expect job polarization to occur in the non-agriculture sector but do not know what the implications are for earning inequality in the country.

Specifically, this paper contributes to the literature in two ways. First, it extends the existing analyses on wage inequality in India to the most recently available data for 2017, which enables us to examine how earnings inequality has changed post-2011.[3] Second, we also extend this work methodologically by decomposing the changes in inequality using semi-parametric methods. This allows us to delineate the role of changing occupational structure, or changing returns to occupations in shaping the observed trends in wage inequality.[4] A simultaneous examination of the two over the last 35 years in India throws up interesting patterns. Contrary to the existing literature that finds a rise in wage inequality in India up to 2004, our analyses show that wage inequality was stable during 2004–11 and showed a distinct decline post-2011 in India. This pattern holds for overall earnings as well as within rural and urban areas. To determine the factors behind the observed evolution in earnings inequality, we then undertake a detailed analyses of changing occupational structure in the urban non-agriculture sector and its implications for the trends in wage inequality.

As discussed earlier, the two most prominent sectors in India have been the IT and construction sectors. The routine task intensity (RTI) for IT professionals is small and they rank first among urban paid workers, excluding agriculture, among the 101 occupations (country-specific measure), and rank in the 98th percentile for average occupational wage. On the other hand, construction ranked in the 86th percentile for RTI and the 12th for the wage distribution in the 1980s. IT professionals come under occupation category 2 of professionals, while construction workers are under category 9 of elementary workers. Both sets of workers have seen rapid employment growth during 2004–17, resulting in job polarization. However, the growth in construction sector employment slowed down post-2011. On the other hand, real earnings growth for IT professionals (and managers at the high end) changed from high growth during 2004–11 to negative post-2011. The growth in earnings of elementary workers also slowed down, but did not decline post-2011. This evidence shows that earnings polarization did not occur along with job polarization. Since growth in employment at the lower end of the RTI distribution was larger post-2004, the average RTI of jobs would have fallen in India, but returns to RTI have been in the opposite direction post-2004. This means that jobs with greater RTI have seen a higher increase in returns in recent years. These findings are at odds with increased demand at the upper end of the skill distribution, resulting in increased earnings at the upper end. This is in contrast to the findings of the existing studies for the USA, where job polarization has been accompanied by earnings polarization.

In India, change in the supply of skilled workers seem to have outstripped change in the demand for skilled workers, resulting in increased employment growth but a decline in earnings growth at the upper end of the skill distribution. At the lower end of the skill distribution, institutional factors like increasing minimum wages may have played an important role. The above descriptive findings are corroborated in the econometric findings. We find that polarization of jobs occurred in urban India post-2004, and increased in pace during 2011–17. However, we do not find evidence for earnings polarization during this period. At the same time, we find that the share of employment in occupations with larger routine task requirements has also fallen in non-agriculture sectors of urban India, with the largest declines during 2004–17. However, we do not find a commensurate decrease in real wages in occupations with

[3] We closely follow the methodology of Gradín and Schotte (2020), which examines similar questions for Ghana.

[4] There are various ways of measuring inequality: earning, wealth, or labour plus non-labour incomes. In this paper, partly because of data availability over time, we focus on changes in earnings inequality (labour incomes in paid jobs).

larger RTI. In fact, we find that occupations with higher routine task involvement have witnessed a larger increase in mean wages, a finding that underscores the conclusion in this study that changing returns to RTI in India have had an equalizing effect on wage earnings.

Lastly, we undertake a decomposition analyses to isolate the effect of changing occupational structure, controlling for other competing factors. The results show that changing demographic workforce structure (like age, gender, education, caste, and religion) and RTI in occupations (i.e. the shift of workers towards less routine occupations) has contributed little to the changing patterns of wage earnings inequality in India. In fact, we find that earnings inequality increased during 1983–2004 and then fell during 2011–17, largely due to changing returns to education and RTI over time. While changes in returns to education had a dis-equalizing effect on wage earnings, changes in returns to routine task content of an occupation had an equalizing effect on wage earnings. Thus, the decomposition analyses confirms our initial findings that mean wages have increased more in occupations with higher routine task content. This has decreased wage earnings inequality in India. However, despite the contribution of changing returns to education and RTI, a large part of the earnings structure remains unassigned to any factor. In general, wage structure in an economy is determined not only by demand and supply conditions, but also by institutional factors such as changes in minimum wage regulations. The findings in this paper show that future research should focus on examining institutional factors that could have possibly resulted in the observed decline in wage earnings inequality post-2004.

This paper expands and contributes to the bigger question of globalization and its implications for wage inequality. While returns to capital and skilled labour have increased over time in the developed countries, its implications for developing countries are not understood very well. Wage inequality in developing countries can change due to forces of trade, technology, and domestic institutional factors. Increased trade could narrow the wage gap between skilled and unskilled workers in developing countries. However, to the extent that skilled labour wages in developing countries are linked to skilled labour wages in developed countries due to technology and mobility of skilled labour, wage inequality can also rise. Lastly, institutional changes in developing countries can also affect wage inequality.

The rest of the paper is organized as follows. Section 2 gives details about the data used in the analyses and elucidates the construction of variables and the broad methodology used for occupational classification and calculation of corresponding RTIs. Section 3 gives a brief overview of the economic and employment structure of India along with discussions on how earnings inequality has changed, job and earnings polarization and changing demand for skills in occupations over the years, and the results from the Shapley decomposition. The results from the recentred influence functions (RIF) based decomposition methods are discussed in Section 4. Conclusions are gathered in Section 5.

2 Data and variable construction

2.1 Data

We use data from the nationally representative employment survey waves in India. These surveys capture age, gender, educational qualifications, and employment status of the sampled individuals, with details about occupation and industry of employment. There have been nine major employment surveys in India since the 1980s: 1983–84, 1987–88, 1993–94, 1999–2000, 2004–05, 2007–08, 2009–10, 2011–12 (called the National Sample Surveys (NSS)) and 2017–18 (Periodic Labour Force Survey (PLFS)). To cover broad time periods, before and after liberalization in India, we choose the following years for our analyses (we refer to each round by the first year throughout the paper): 1983, 1993, 2004, 2011, and 2017. The NSS surveys are comparable to the PLFS surveys in methodology, design, and the variables on which data are collected.[5] We use data for working-age adults who were 15–64 years of age at the time of survey who worked either as paid employees (salaried/casual labourer) or self-employed (employer or unpaid family helper) for the majority of the time in the last year (at least six months), and use the primary activity or occupation of work. The weekly earnings schedule records the earnings in the last reference week for paid workers (casual/salaried) and is taken as our main earnings variable.[6]

One key point to note is that earnings for self-employed workers are not captured in any survey apart from the PLFS 2017. Thus, we focus on trends in earnings for paid workers at the overall level but check the robustness of our main findings to imputed earnings for self-employed urban workers for rounds before 2017, based on the methodology discussed in Appendix A.[7] Additionally, in 2017–18 the earnings of salaried workers were captured by asking them about their earnings in the last month. These were converted to weekly earnings by dividing the monthly earnings by 4.3. As mentioned, since earnings for the self-employed are not captured in four out of five data rounds, we focus on the paid employees for earnings results. All earnings data are deflated and reflect real values in 2017 INR. For urban India we use the Consumer Price Index for Industrial Workers (CPIIW) and for rural workers we use the Consumer Price Index for Agricultural Laborers (CPIAL) at the all-India level to generate real earnings. All analyses are weighted using survey weights.[8] Further, we restrict the sample to paid urban workers in the non-agriculture sector for the main analyses due to two reasons. First, it is difficult to gauge the role of the changing occupation structure in an economy that is predominantly agricultural. The main pattern here is movement away from agriculture to non-agricultural occupations. Second, the RTI values for agricultural operations vary the most across the two RTI measures used (discussed later), and agriculture forms a small proportion of overall employment in the urban sector. Moreover, patterns of inequality change in non-agriculture sector occupations in urban areas are consistent with the overall patterns in urban areas.

2.2 Construction of variables

2.3 Matching occupational classifications across surveys

The National Classification of Occupation 1968 (NCO-68), which is a variant of the International Standard Classification of Occupations (ISCO), is used in employment data collected in 1983, 1993, and 2004 for recording the occupational classification of each employed person. In the years 2011 and 2017, NCO-04 was used. NCO-68 has five-digit codes, of which the first three digits were used for recording information in the survey instruments. NCO-04, however, used six-digit codes and the first three digits were used for recording information in the survey. A concordance was generated across NCO-68 and NCO-04 at the three-digit level. While NCO-68 recorded 458 occupations at the three-digit level, NCO-04 recorded 113 occupations at the same level. Thus, multiple 1968 codes can be matched to a single NCO-04 code. The concordance between NCO-04 in India and ISCO-88 was the next step.[9]

[5] One departure point is the stratification methodology, which changed to give adequate representation to all education groups in 2017. But this has no bearing on population estimates since all estimates are weighted by sampling weights provided in each round.

[6] Since we use the earnings of persons primarily employed in the labour market, the results do not differ if daily earnings are calculated by dividing weekly earnings by days worked in the last week.

[7] We do not impute the earnings for rural self-employed workers because a large proportion of these work in the agriculture sector and therefore the imputation is likely to be unreliable. India, being a developing country, has a large proportion of the workforce engaged in the agriculture sector in rural India, which makes imputation of earnings for the rural workforce difficult and also results in a highly skewed occupational structure at the overall country level towards agriculture.

[8] The outliers at the lower end of the earnings distribution were capped at the first percentile (Rs.99.4) for paid employees.

[9] Here, armed forces could not be mapped to any NCO-04 code and was dropped from the analyses. Also, NCO-04 code 233 was matched to multiple ISCO-88 codes (233, 234, and 235). The concordances generated at each level are available in the Technical Appendix to the paper.

2.4 Mapping task content to occupations

We use two alternative data sources to measure the task content of each occupation.

*O*NET RTI measure*

We match each occupation (which is now at the ISCO-88 three-digit occupation level) to the task measures derived using the O*NET 2003 database (the methodology is based on Acemoglu and Autor (2011)). The O*NET database gives task content for occupations in the USA using the Standard Occupational Classification (SOC-00). This is done because no survey data on occupational tasks have been collected for India so far. The existing literature has used the mapping to the US occupation–task contents to overcome this data gap across countries (Hardy et al. 2018). This measure can be noisy to the extent that task content can differ across countries.[10]

Country-specific RTI measures

Recent research by Lewandowski et al. (2019) shows that the same occupation can have a different skill-set requirement across countries with varying income levels. Lewandowski et al. (2020) predict the country-specific RTIs of occupations based on survey data collected in 46 countries covering low-, middle- and high-income economies. They indeed find that similar occupations in the low- and middle-income countries are more routine intensive than in high-income countries. There is no country-specific survey that measures the extent of routine tasks across occupations in India, and given that it is a low- to middle-income country, the RTI for the same occupation is likely to be higher in India than in the USA for which O*NET data are available. We thus use an India-specific measure for task content of occupations, constructed by Lewandowski et al. (2020), and refer to this as a country-specific measure of RTI. The country-specific task measure for India is constructed at the two-digit occupational classification level and matched to the Indian employment data. We also rescale the two-digit country-specific RTI measures using the three-digit level variation from the O*NET RTI measures to check the robustness of our results.

We use the above two mappings of occupations to tasks (O*NET and the country-specific measure) and construct a measure of RTI using the methodology in Autor and Dorn (2009) and Goos et al. (2014). The four task measures—routine cognitive, routine manual, non-routine cognitive (analytical), and non-routine cognitive (interpersonal) are used to define the RTI measure:[11]

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

3 Background: trends in earnings inequality and employment

3.1 Economic context

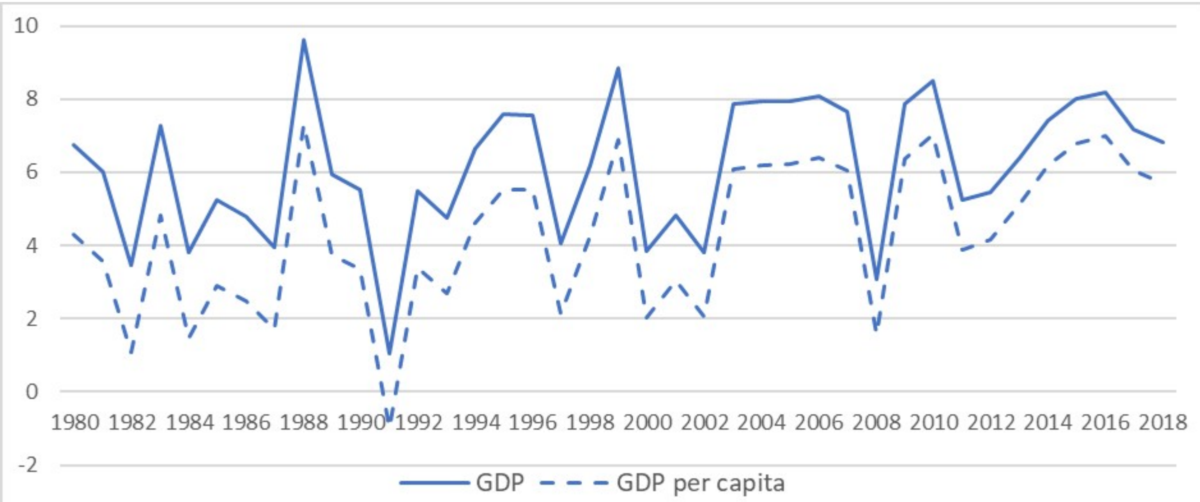
India is the world's third-largest economy in purchasing power parity (PPP) terms, having US$11.33 trillion gross domestic product (GDP) and 7.98 per cent share of the world's GDP in 2019 (figures from the IMF). India's GDP has seen significant growth post-1980s. During the period 1980–90, the average

[10] The crosswalk between SOC-00 and ISCO-88 was provided by the Institute for Structural Research. A few ISCO codes present in the Indian data were not present in the O*NET data. These were matched to the nearest available codes for which RTIs are available in O*NET (ISCO-88 codes 111, 324, 334, and 912, matched to codes 112, 323, 333, and 913, respectively).

[11] The lowest score in the sample is added to the scores of all individuals and an additional 0.1 is added to avoid negative values in the logarithm. We take the US weights and deviations from the mean calculated using US data when using the O*NET data.

GDP growth rate was 5.7 per cent per annum, with the highest growth rate of 9.63 per cent in 1988. Post-1991 liberalization reforms, the country recorded a GDP growth rate of more than 6 per cent for most years. There was commensurate growth in GDP per capita at 3.34 per cent per annum from 1980 to 1990, and at 4.72 per cent per annum from 1991 to 2018. The Indian growth experience has been different from the other Asian countries that saw export-led growth. Its growth is based on the services sector boom in the country. During 2004–08, the average growth rate reached a high of 8 per cent per annum. This was because of domestic factors like liberalization in the 1990s leading to substantial reforms across sectors, and external factors such as the global economic boom. But it slowed due to the 2008–09 financial crisis, reducing investment, manufacturing, and exports. The momentum of the spectacular GDP growth during most of the 2000s at around 6–8 per cent per annum (among the highest in the world) has slowed down since 2017. The post-2011 period has seen commensurately little growth in jobs despite moderate GDP growth rate (Figure 1).

Figure 1: Annual growth rates of real GDP and real GDP per capita,1980–2018



Source: authors' construction based on World Bank national accounts data.

Over the years, India has undergone a structural transformation in sectoral income shares. The share of agriculture and allied activities dropped from 35.69 per cent in 1980 to 29.53 per cent in 1990 and 14.39 per cent in 2018, while the share of services increased from 37.65 per cent in 1980 to 42.55 per cent in 1990 and 54.15 per cent in 2018. However, the decline in agriculture's share in income has not been commensurate with the decline in its share of employment. Around 40 per cent of rural Indian employment (which covers about 70 per cent of the Indian population) is still based on agriculture activities. India, despite being a labour-surplus economy, did not see a take off in the labour-intensive sectors like textiles. Emerging new sectors in services like IT have not been able to pull employment from the agriculture sector. Thus, the new jobs created were mostly in the informal sector, with lower earnings and nearly no social protection (Papola and Sahu 2012). Despite India's high GDP growth, which has petered out lately, the economy faces an employment crisis. In 2018, 50 per cent of the population was in the labour force, out of which 81 per cent were employed in the informal sector.[12] Rising education levels with little growth in employment has resulted in swelling numbers of educated-unemployed youth in 2017–18.

There has been a steady decline in the proportion of Indians living in poverty (Table 1).[13] During 1983–93, the percentage of poor declined by 9 percentage points. Poverty reduction in India, especially in the 1990s, was observed mainly through labour productivity growth. It improved via two channels: first,

[12] https://thewire.in/labour/nearly-81-of-the-employed-in-india-are-in-the-informal-sector-ilo.

[13] The estimates are based on the poverty line of US$1.90 per person per day.

increasing returns to labour in agriculture; and second, shifting of employment from agriculture to higher productive sectors like construction (Ahsan et al. 2010). The proportion of poor further reduced from 45.9 per cent in 1993 to 38.2 per cent in 2004 and 21.2 per cent in 2011. The proportion of people living in poverty was greater in urban areas than in rural areas as per national estimates, which has reversed since 2004.

Table 1: Poverty headcount ratio (percentage of population) and Gini Index, 1983–2011

Year	World Bank estimate (2011 PPP)		National estimate (poverty line)			Gini index
	US$1.90 a day	US$3.20 a day	National	Urban	Rural	
1983	54.8	85.5	44.48	45.65	40.79	32.1
1987	48.9	82.8	n.a.	n.a.	n.a.	32.6
1993	45.9	81.1	35.97	37.27	32.36	32.7
2004	38.2	75.2	27.50	28.30	25.70	36.8
2009	31.1	69.9	29.80	20.90	33.80	37.5
2011	21.2	60.4	21.92	13.7	25.7	37.8

Note: in India, poverty estimates are based on consumption data. From 1983 to 2004, poverty estimates are based on the URP method, in which respondents are asked to detail consumption over the previous 30 days. The years 2009 and 2011 are based on the MRP method, in which five low-frequency items (clothing, footwear, durables, education, and institutional health expenditure) are surveyed over the previous 365 days and all other items over the previous 30 days.

Source: authors' compilation based on World Bank data (including Gini) and national estimates of poverty from the Reserve Bank of India.

The trends in inequality depend on the measures used—consumption or total income (salaried/casual earnings plus self-employed earnings). The Gini index in Table 1 presents the consumption-based inequality measure, which saw a large increase between 1993 and 2004 (by almost four points). Thereafter, there has been some increase till 2011, but only very moderate, by one point. The income-based Gini index derived using the Indian Human Development Survey (IHDS) shows a modest increase during 2004–11, from 0.53 to 0.55, an increase of two points (Himanshu 2018). On average, despite the trends, the level of inequality in India is large. In the next section we discuss the trends in earnings-based inequality for paid workers.

3.2 Trends in earnings inequality and occupational structure in India

Changes in aggregate earnings inequality

We document the changes in weekly wage earnings inequality in India for paid workers over the last three decades.[14] Table 2 shows the Gini coefficient, variance of earnings, and interquantile ratios for all areas, and separately for urban and rural areas. There is pro-rich growth during 1983–2004, with an increase in the overall Gini from 0.52 to 0.56, but this reversed during 2004–17 and fell from 0.56 to 0.51 and further to 0.45. Hence, we see an overall decline in paid earnings inequality during 1983–2017, but the trends differ by sub-period under consideration. Also, there are differences by location in changes in earnings inequality at the lower (50th to 10th percentile) and higher ends (90th to 50th percentile) of the distribution. For rural areas, inequality has declined over the entire period at both the ends; in urban areas, inequality has declined at the lower end and increased at the upper end. However, there is a perceptible decline since 2004 in urban areas at the upper end of the earnings distribution as well. The patterns for inequality changes in urban areas, excluding agriculture, mimic the overall patterns well. We thus examine wage earnings inequality patterns in detail for urban areas now.

[14] As a robustness check, we also impute earnings of self-employed workers in urban areas and find that the results from all analyses conducted in the paper are similar when self-employed persons are included. Appendix A details the imputation procedure. The results are omitted for brevity.

Table 2: Interquantile ratios and summary inequality indices

	1983	1993	2004	2011	2017
Panel A: all areas					
ln(q90)–ln(q10)	2.516	2.533	2.565	2.234	2.100
ln(q90)–ln(q50)	1.445	1.503	1.600	1.337	1.180
ln(q50)–ln(q10)	1.070	1.030	0.965	0.896	0.920
Var(log earn)	0.853	0.919	0.936	0.743	0.648
Gini(log earn)	0.084	0.082	0.078	0.064	0.059
Gini(earn)	0.520	0.524	0.558	0.505	0.452
Panel B: urban					
ln(q90)–ln(q10)	2.100	2.339	2.547	2.314	2.120
ln(q90)–ln(q50)	0.868	1.066	1.449	1.397	1.253
ln(q50)–ln(q10)	1.232	1.273	1.099	0.916	0.868
Var(log earn)	0.712	0.871	0.945	0.856	0.663
Gini(log earn)	0.068	0.071	0.073	0.067	0.058
Gini(earn)	0.419	0.443	0.512	0.507	0.447
Panel C: rural					
ln(q90)–ln(q10)	1.966	1.983	1.946	1.609	1.666
ln(q90)–ln(q50)	1.050	1.063	1.030	0.790	0.819
ln(q50)–ln(q10)	0.916	0.920	0.916	0.820	0.847
Var(log earn)	0.562	0.609	0.648	0.503	0.513
Gini(log earn)	0.071	0.069	0.067	0.054	0.054
Gini(earn)	0.450	0.438	0.479	0.404	0.397
Panel D: urban (non-agriculture sector)					
ln(q90)–ln(q10)	2.079	2.197	2.447	2.335	2.097
ln(q90)–ln(q50)	0.856	1.019	1.386	1.419	1.253
ln(q50)–ln(q10)	1.224	1.179	1.061	0.916	0.844
Var(log earn)	0.656	0.830	0.911	0.844	0.652
Gini(log earn)	0.064	0.068	0.071	0.066	0.057
Gini(earn)	0.404	0.429	0.504	0.503	0.444

Note: the sample includes paid workers.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

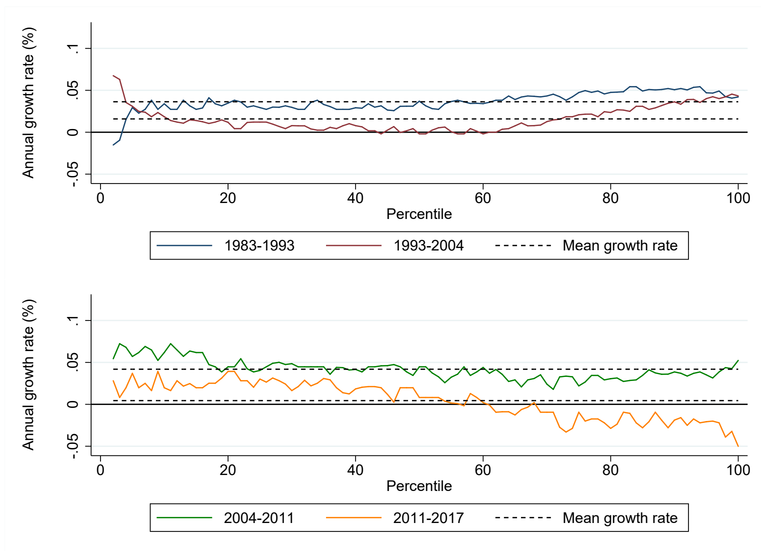
Next, we plot the growth incidence curves for weekly earnings by percentiles for urban areas (Figure 2). These figures show growth in mean earnings for each wage percentile during different time periods. The trends here confirm the findings of inequality measures discussed previously, and that wage inequality trends differ by sub-period. We observe that during 1983–2004 (a period of lower economic growth), higher growth in wage earnings was observed at the top of the wage earnings distribution. This pattern reversed during 2004–17 and lower growth in wage earnings occurred at the top of the earning distribution and higher wage earning growth at the bottom of the earnings distribution. We observe similar patterns in rural (omitted for brevity) and urban areas, but it is more pronounced for urban workers. The main take-away from the above analyses is that following an increase in paid earnings inequality up to 2004, there has been a clear reduction in earnings inequality in India post-2004. This pattern in wage earnings inequality change holds for both men and women.

The above findings may appear at odds with the consumption inequality estimates shown in Table 1 and also discussed in earlier work by Dang and Lanjouw (2018) and Chancel and Piketty (2019).[15] There are no comparable consumption data for years post-2011 to verify what happened to consumption inequality post-2011. Notably, the growth in consumption inequality slowed drastically during 2004–11 compared to the previous decade, a trend that also holds for paid earnings inequality. There are, however, a few

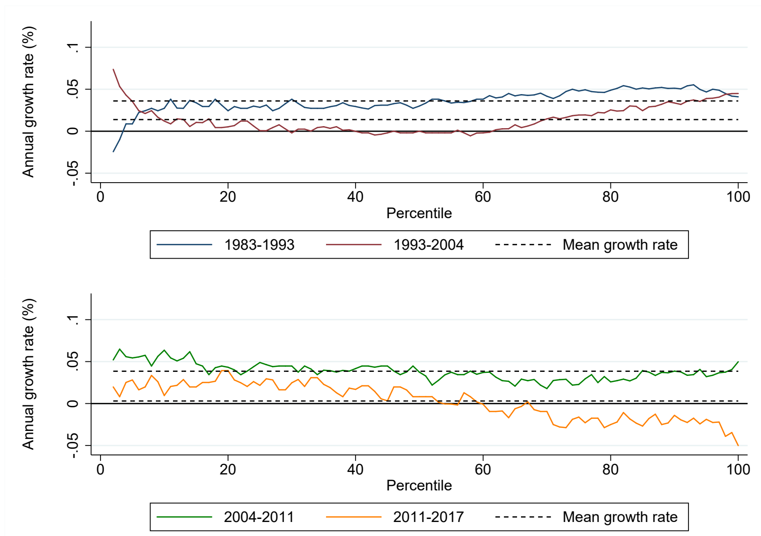
[15] Chancel and Piketty (2019) show that the top 1 per cent of earners captured less than 21 per cent of total income in the late 1930s; this reduced to 6 per cent in the early 1980s, but rose to 22 per cent in the recent period between 1980 and 2015.

differences between our inequality measure and those used in the literature. First, both consumption and income data are measured at the household level, while paid earnings are measured at an individual level, for those who are working. Therefore, our inequality estimates are not directly comparable to either consumption or income inequality measures at the household level. Falling earnings inequality could still create higher consumption inequality at the household level because of rising assortative mating and women's decisions to work in the labour market as their level of education increases. Second, the measure of income inequality using IHDS data or National Accounts Statistics includes capital earnings and wealth measures, which are not included in the paid worker earnings in our measure of inequality.

Figure 2: Growth incidence curves: urban India
(a) Urban (paid)



(b) Urban (paid, non-agriculture)



Note: percentiles are based on the earnings arranged in ascending order, which will have the same earnings' percentile rank across all years.

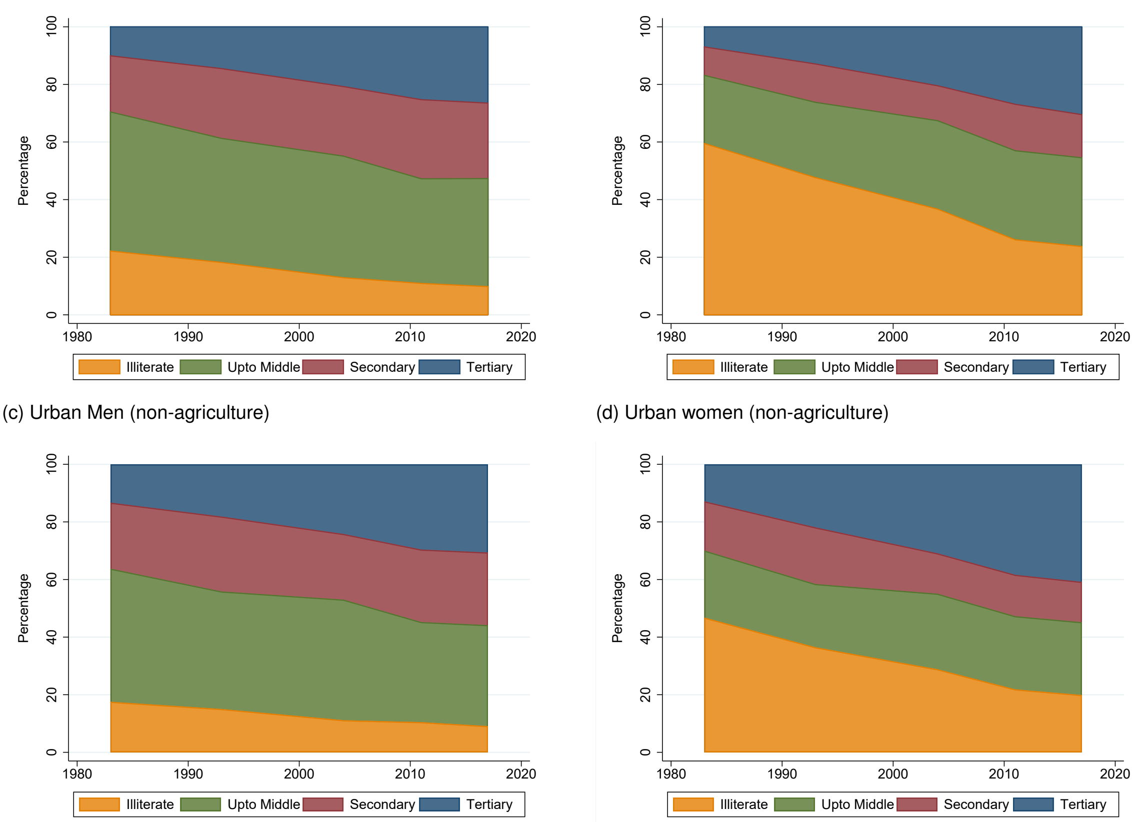
Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Changes in educated workers and education earnings premium

Figure 3 show the education composition of the urban workforce and how it has changed over the years for men and women.[16] We clearly see that over the years the workforce has become more educated. The gradient of increase is sharper for women than for men. The proportion of illiterate women in the urban workforce has fallen from 60 per cent in 1983 to 22 per cent in 2017. The proportion of women with tertiary education has increased from 3 per cent in 1983 to 30 per cent in 2017. For men, the reduction in illiterate workers in urban areas has been made up by an increase in the proportion of men in tertiary education. Among the rural male workforce, the decline in illiterate workers has been compensated by an increase in secondary-educated male workers. These trends show that supply of workers with secondary and tertiary education has risen in India over the last three decades.

Figure 3: Changes in educational structure of the workforce: urban workers

(a) Urban men (b) Urban women (c) Urban Men (non-agriculture) (d) Urban women (non-agriculture)



Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

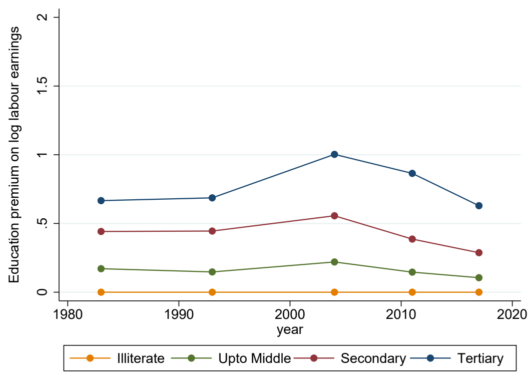
Given the increasing supply of educated workers, it is instructive to look at the changing education premium over time. Figure 4 shows the returns to different education levels for each year and how they are changing over time for men and women in urban areas. The figures plot the education coefficients after controlling for sociodemographic characteristics like age, religion, caste, and Indian state of residence. Occupational structure is added as a control at the two-digit level. Urban areas show an increase in the education premium for those having secondary and tertiary education until 2004, and thereafter the premium declines with respect to the illiterate category during 2004–11. For women, the fall for secondary-educated workers began earlier (post-1993). These findings are evidence of supply of educated workers outstripping demand, or even due to worsening quality in the higher-educated workforce following the huge push in education during the 2000s in India. If anything, women have borne the brunt of the declining premiums. Overall, there seems to have been slower growth in real earnings since

[16] The trends are similar when excluding the self-employed, and these graphs have been omitted for brevity.

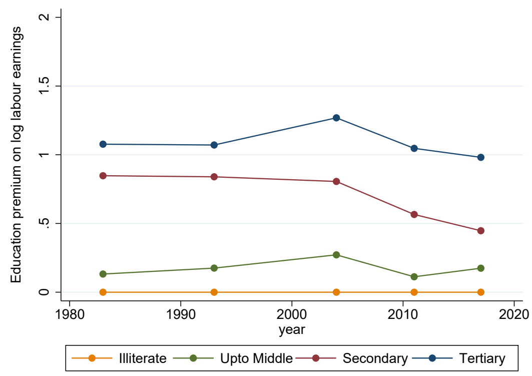
2011, especially for secondary- and tertiary-educated workers, consistent with increasing unemployment rates in urban areas for educated workers post-2011. However, the earnings premium across individuals having some education (i.e. between middle/secondary/tertiary education categories) shows differential trends, depending on the category concerned. For instance, for urban non-agriculture workers (both men and women) the premium between tertiary–secondary and tertiary–middle increased during 1983–2017. A detailed analysis by sub-period shows that post-2004 there was some decline (for example, from 49 to 39 per cent for tertiary–secondary and from 77 to 59 per cent for tertiary–middle during 2011–17 for urban, paid, non-agricultural workers) but largely the education premium across middle/secondary/tertiary education categories has remained stable.

Figure 4: Education premium on weekly earnings (controls: education, sociodemographic, occupation)

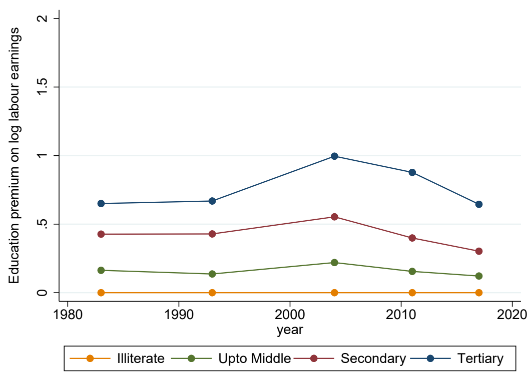
(a) Urban men (paid)



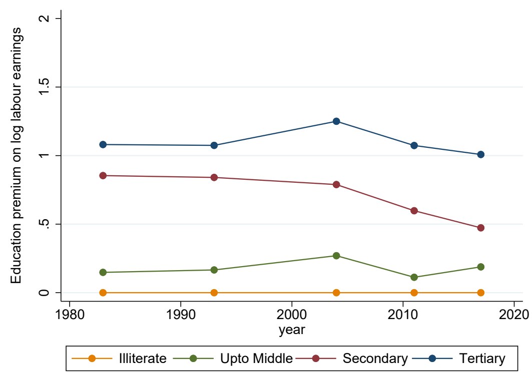
(b) Urban women (paid)



(c) Urban men (paid, non-agriculture)



(d) Urban women (paid, non-agriculture)



Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Changes in employment structure of the workforce

We now look at the changes in workforce structure in India over time by type of employment in Table 3 and by industry of employment in Table 4, in both rural and urban areas. We find that paid workers form about 43 per cent of the total workforce in rural areas and about 60 per cent of the workforce in urban areas. These proportions have largely remained stable over the years. Among the self-employed non-agricultural workers, many do not have any employees under them in either urban or rural areas, and thus are likely to be small, informal workers who are self-employed. The unpaid workers largely reflect family workers who work in a family enterprise but are not paid for it. In rural areas these numbers are large for the agriculture sector, reflecting unpaid workers on family farms. Lastly, the agriculture sector dominates employment for both paid workers and self-employed in rural areas. On the other hand, in urban areas non-agriculture sectors dominate workforce employment. In rural India, the majority of workers are still employed in agriculture, despite a fall in agricultural employment over time. Therefore, any analyses for rural India are likely to be completely dominated by them.

Table 3: Changes in type of workers (paid vs self-employed; %)

Employment status	1983	1993	2004	2011	2017
			Panel A: urban		
Paid employees					
Agriculture	5.16	4.85	2.75	2.11	2.01
Non-agriculture	56.03	55.63	54.18	57.75	61.04
Subtotal	61.19	60.48	56.93	59.86	63.04
Non-agriculture					
Self-emp. w/ employees	0.00	2.21	2.25	2.05	2.68
Self-emp. w/o employees	25.87	24.88	27.96	27.74	26.27
Unpaid workers	6.14	7.10	8.34	6.69	4.43
Subtotal	32.01	34.19	38.54	36.48	33.38
Agriculture					
Self-emp. w/ employees	0.00	0.30	0.18	0.18	0.25
Self-emp. w/o employees	4.78	3.07	2.54	2.29	2.48
Unpaid workers	2.03	1.96	1.81	1.19	0.86
Subtotal	6.81	5.33	4.53	3.66	3.58
			Panel B: rural		
Paid employees					
Agriculture	32.64	33.51	28.21	23.52	16.11
Non-agriculture	10.55	12.53	15.55	23.49	27.89
Subtotal	43.19	46.04	43.76	47.01	44.01
Non-agriculture					
Self-emp. w/ employees	0.00	0.26	0.21	0.28	0.60
Self-emp. w/o employees	8.06	8.64	10.95	11.72	12.23
Unpaid workers	2.02	2.45	3.08	2.44	1.50
Subtotal	10.09	11.35	14.24	14.44	14.33
Agriculture					
Self-emp. w/ employees	0.00	1.52	0.67	0.77	0.86
Self-emp. w/o employees	29.88	21.86	20.97	22.05	26.51
Unpaid workers	16.84	19.22	20.35	15.72	14.29
Subtotal	46.72	42.61	42.00	38.55	41.67

Note: the sample includes all workers.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Table 4 further shows the changes in share of workers by industry. In rural areas, the trends are dominated by the agriculture sector, with a large fall in the agricultural workforce and an increase in the construction workforce. In urban areas, there is a fair distribution across various industrial sectors. Again, over time agricultural employment has fallen in urban areas and employment in construction has increased. Construction jobs are at the low end of the earnings spectrum and have seen a large increase over time. Largely, workers moving out of agriculture but not having the education or training for high-skilled occupations are moving into construction sector jobs since manufacturing (which is located at the middle of the earnings distribution in India) has seen a fall in employment share over time. There has also been an increase in the workforce in wholesale and retail trade in urban areas, while other services form a large proportion and have remained stable over time. These findings hold for paid workers as well, and also show that looking at urban India for a further analysis of how the nature of jobs is changing in India is the most useful. We henceforth concentrate on urban paid workers for occupational analyses since we have seen that rural employment in India is still predominantly agricultural. Also, within urban paid workers we look at only those who are employed in the non-agriculture sector for two reasons: (1) in urban areas the agriculture workforce forms a small proportion of the total workforce; and (2) measuring RTI for the agricultural workforce seems to be more error prone, as discussed earlier.

Table 4: Changes in industry share of workers (%)

	1983	1993	2004	2011	2017
Panel A: urban					
Agriculture and fishing	14.3	13.1	9.1	7.6	7.2
Mining and quarrying	1.4	1.3	0.9	0.9	0.6
Manufacturing	32.8	29.0	29.4	29.8	29.5
Construction (other industry)	5.8	7.9	10.1	13.4	15.1
Wholesale and retail trade	14.6	16.0	19.9	15.2	15.0
Other services	31.2	32.6	30.6	33.1	32.6
Panel B: urban paid					
Agriculture and fishing	11.0	11.6	7.0	5.3	4.4
Mining and quarrying	2.2	1.9	1.5	1.4	0.8
Manufacturing	34.7	31.6	31.4	29.5	29.6
Construction (other industry)	6.6	10.0	12.9	17.5	18.8
Wholesale and retail trade	6.7	7.5	10.3	9.3	10.3
Other services	38.8	37.4	36.8	37.0	36.1
Panel C: rural					
Agriculture and fishing	81.1	79.5	73.0	63.1	57.6
Mining and quarrying	0.7	0.8	0.7	0.8	0.6
Manufacturing	8.5	8.3	9.6	10.0	9.8
Construction (other industry)	2.8	3.5	7.3	16.9	20.5
Wholesale and retail trade	1.6	1.9	3.1	2.1	2.5
Other services	5.3	5.9	6.2	7.2	8.9

Note: the sample includes all workers (paid and self-employed).

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Table 5 shows the occupation-level changes in employment and earnings at the one-digit level of the occupational classification for urban paid workers in non-agricultural sectors.[17] It can be seen that over time there has been an increase in employment share of managers and professionals at the upper end and in services at the mid-level (retail, tourism-related mostly), while clerical jobs at the mid-level and machine operators at the low-skill level have fallen. Elementary workers, especially the share of construction workers, has increased post-2004. There was a rise in the *Trades* workforce share during 1983–2017, but this fell during 2004–17 along with a decline in the rate of increase for services. These trends clearly point to a reduction in the workforce in sectors more amenable to automation. On the other hand, movement in wages differs across the sub-periods. During 1993–2004 the rise in weekly earnings was the highest for managers, professionals, and technicians, but during 2004–11 the growth in wages in these occupations fell relative to those in elementary or mid-skill occupations. In fact, during 2011–17 the real earnings for managers and professionals fell by 6.3 and 4.1 per cent per annum, respectively. Notably, wage earnings growth is determined by both demand and supply of skills. While the demand for high-skilled jobs has increased over time, an increase in supply of high-skilled workers exceeding the increase in demand can lead to decline in wage earnings for the skilled sector.

[17] The non-agriculture workforce is kept on the basis of industrial classification. However, we still find that a few report themselves under the skilled agriculture occupation even after we drop those employed in the agricultural industry.

Table 5: Changes in employment and earnings: main occupational groups (urban non-agriculture, paid)

		Levels					Percentage growth (annual)			
		1983	1993	2004	2011	2017	1983–93	1993–2004	2004–11	2011–17
		Panel A: employment share (%)								
1	Managers	2.3	3.3	3.6	4.7	5.9	3.7	0.4	3.7	3.9
2	Professionals	6.7	7.6	7.3	11.0	12.4	1.3	–0.2	6.0	2.0
3	Technicians	9.7	10.5	9.4	9.3	9.6	0.8	–0.5	–0.1	0.4
4	Clerks	11.9	11.0	9.1	8.8	7.1	–0.7	–0.9	–0.4	–3.6
5	Services	11.9	11.6	15.4	13.6	15.2	–0.3	1.4	–1.7	1.8
7	Trades workers	23.6	23.6	27.4	21.0	19.0	0.0	0.7	–3.7	–1.7
8	Machine operators	13.4	12.8	11.1	12.2	10.7	–0.5	–0.7	1.3	–2.2
6	Skilled agricultural	0.4	0.4	0.3	0.3	0.2	0.4	–2.2	0.0	–2.3
9	Elementary	20.1	19.2	16.5	19.1	20.0	–0.5	–0.7	2.2	0.8
		Panel B: mean weekly earnings (INR, constant 2017 prices)								
1	Managers	3,758.9	6,026.6	9,979.1	11,743.7	7,922.9	4.8	2.4	2.4	–6.3
2	Professionals	3,091.8	4,591.1	7,110.3	8,377.5	6,505.2	4.0	2.1	2.4	–4.1
3	Technicians	2,190.4	3,442.1	4,968.4	5,484.8	5,368.4	4.6	1.8	1.4	–0.4
4	Clerks	2,039.6	3,237.5	4,407.5	4,820.0	4,568.6	4.7	1.5	1.3	–0.9
5	Services	1,144.5	1,711.6	2,095.3	2,741.4	2,539.0	4.1	1.0	3.9	–1.3
7	Trades workers	1,163.9	1,711.5	1,813.1	2,325.9	2,331.4	3.9	0.3	3.6	0.0
8	Machine operators	1,585.5	2,151.4	2,486.0	2,907.4	2,849.2	3.1	0.7	2.3	–0.3
6	Skilled agricultural	1,320.0	2,443.5	2,376.1	2,223.8	2,575.4	6.4	–0.1	–0.9	2.5
9	Elementary	1,011.7	1,291.3	1,449.8	1,779.8	1,912.3	2.5	0.6	3.0	1.2

Note: the sample includes urban non-agricultural paid workers.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Changes in average RTI over time

The above changes in occupational structure show that over time there has been a clear increase in high-skill jobs like managers and professionals with some increase in retail and tourism service-related jobs and construction jobs. This shift implies a larger increase in non-routine jobs over time. Therefore, we next calculate the RTI of jobs and examine how the average RTI changed over the last three decades in India. The results are presented in Table 6 and show that the average RTI has decreased over time in India for both O*NET and country-specific RTI measures. On average, the O*NET measure (from 0.55 to 0.43) shows a larger decline in RTI than the country-specific measure (from 0.46 to 0.40).[18] We also check the average RTI by occupation groups in India using the 1983 weights at the three-digit level to aggregate at the two-digit level for both O*NET and country-specific RTI values. One group that gives drastically different values using the two RTIs is agricultural workers. For instance, for urban paid workers, while agricultural workers are given a standardized RTI score of 0.36 (skilled agriculture) and 0.55 (agricultural labourers), the corresponding values using country-specific RTIs are 1 and 1.07, respectively. First, the distinction between these two categories of agricultural workers is very subjective and there could be errors in occupational classification. Second, the ranking of agricultural labourers is very different across the two definitions—they rank in the middle using the O*NET measure and at the top using country-specific RTI values. Thus, we also drop agriculture from our further analyses. Agricultural labourers have the lowest earnings in India and hence both of these groups fall at the lowest end of the earnings distribution; due to a structural change away from agriculture, there has been a natural movement away from agriculture in India, as discussed earlier.

[18] There is an unexpected increase in RTI value during 2004–11 using the O*NET measure. This is driven by within-occupation increases in RTI measures at the one-digit level, which is especially large for craft and related workers at the lower end and somewhat for managers at the upper end of the skill spectrum.

Table 6: Change in average RTI: paid, non-agriculture, urban

Year	O*NET RTI	Country-specific RTI
1983	0.55	0.46
1993	0.48	0.43
2004	0.45	0.44
2011	0.51	0.41
2017	0.43	0.40

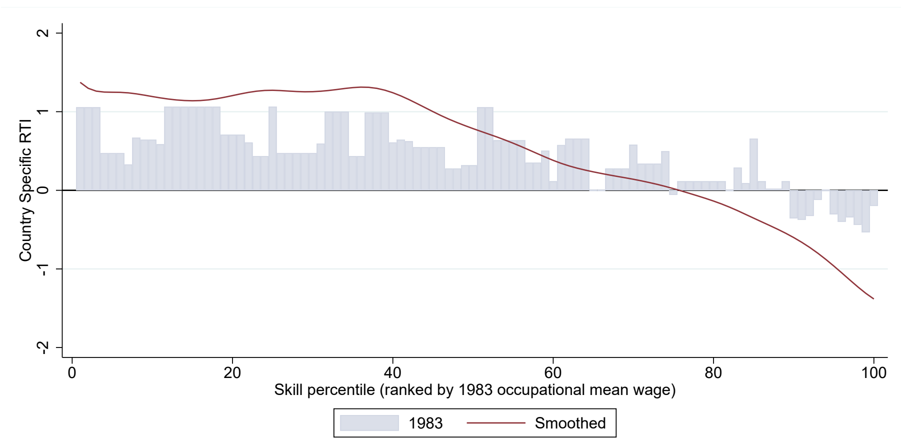
Note: the sample includes urban non-agricultural paid workers. Country-specific RTI at the two-digit level and O*NET RTI at the three-digit level is used.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

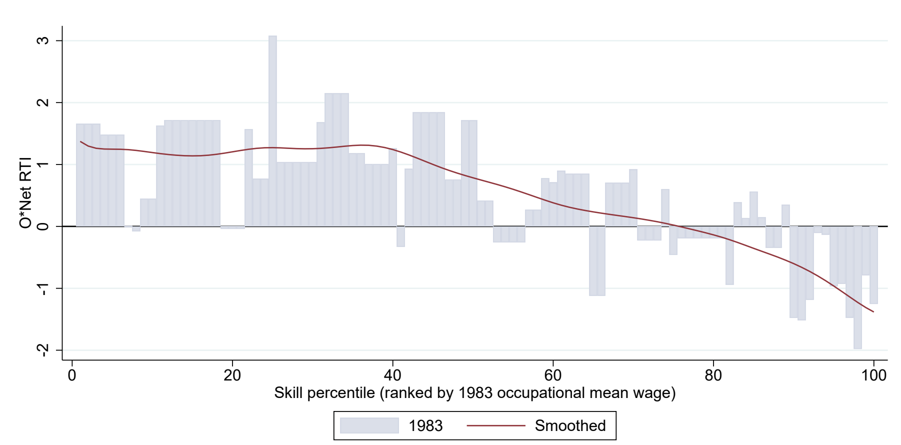
Since the main focus of the paper is to look at the nature of future jobs, dropping the agriculture sector seems a natural choice for developing countries. For example, even if there is job polarization, our estimates may not capture it when agricultural workers are included as they will form the bottom rung of occupations across the earnings distribution, and have also undergone a fall in employment proportion over time. Figure 5 shows the RTI and how it varies across the earnings percentiles using both the O*NET and the country-specific measures in 1983 (i.e. the base year of the analyses). As expected, we find that RTI falls along the wage distribution using both measures of RTI. The routine task requirement in higher-paying jobs is smaller.

Figure 5: **Routine task intensity across earnings percentiles by year (urban, paid, non-agriculture)**

(a) Country-specific RTI



(b) O*NET RTI



Note: the sample includes urban non-agricultural paid workers.

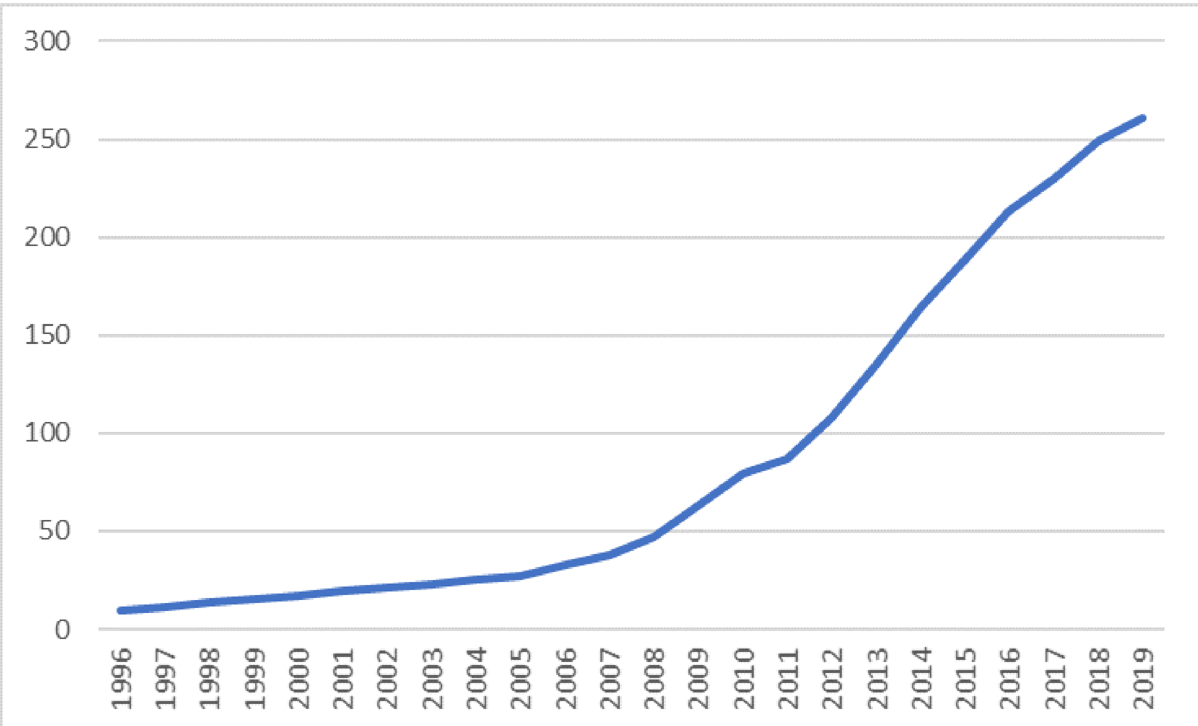
Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Changes in minimum wage and other institutional factors in India

Two types of workers have seen an increased demand in urban India. One is construction labourers at the lower end of the skill spectrum; the other is managers and professionals. High-skilled IT workers have also seen increased demand due to outsourcing of these services to India. Among the 101 occupations in our analyses, IT professionals hold first position, while mining and construction labourers hold 86th position (using the country-specific RTI percentile, excluding agriculture in urban areas). Therefore, our initial hypothesis about IT having low RTI and construction having a higher RTI can be seen in the RTI ranking as well. In the skill percentile ranking (wage percentiles), in 1983 the occupational mean wage for mining and construction labourers was at 12th position, while that for IT professionals was at 98th among urban paid workers, excluding agriculture. The returns to these two types of workers are evolving differently. The real earnings for IT workers have taken a hit since 2011, and in fact have fallen post-2011, while they had slowed in growth during 2004–11, whereas those of construction labourers have risen consistently. These patterns also point to a demand–supply skills gap in India. The earnings for construction workers are linked to minimum wages, and these have also been rising in the country post-2004.

India has one of the largest numbers of minimum wages, with 1,709 categories set by the state governments and 45 categories set by the central government. There are variations in minimum wages for the same occupation across states, which to a certain extent reflects the disparities in living costs across states. We compile data on minimum wages in agriculture (since agriculture is the sector with the lowest daily wage and is likely to represent the floor for wages in India) across states, starting in the mid-1990s, for which the data are available from Labour Bureau reports in India. The average of these minimum wage rates is plotted in Figure 6. The figure clearly shows that post-2004 there has been an exponential increase in the real daily minimum wage for agricultural workers in India. The rapid increase in wages could have resulted in a decline in wage inequality.

Figure 6: Real minimum daily wage in India: agriculture (INR)



Source: authors' calculations based on Labour Bureau reports for India (various years).

3.3 Is earnings inequality affected by the changing nature of occupations and skills?

Regression-based evidence: job polarization

We conduct a regression-based test for job polarization in India (Goos and Manning 2007) using a quadratic specification in initial log mean weekly earnings at the three-digit occupational classification. The below equations are estimated for polarization in employment and earnings:

$$\Delta \log(E_{j,t}) = \beta_0 + \beta_1 y_{j,t-1} + \beta_2 y_{j,t-1}^2 + e_1$$

$$\Delta \log(y_{j,t}) = \pi_0 + \pi_1 y_{j,t-1} + \pi_2 y_{j,t-1}^2 + e_2$$

where $\Delta E_{j,t}$ is change in employment in occupation j during the period t and $t-1$ and $\Delta \log(y_{j,t})$ is change in weekly earnings in occupation j during period t and $t-1$. Here, $y_{j,t-1}$ is earnings in occupation j in time period $t-1$. Both equations are estimated by weighting each occupation j by its initial employment share so that results are not biased by changes in composition of small occupation groups.

Table 7: Polarization in employment and earnings: paid, non-agriculture, urban

	(1) 1983–93	(2) 1993–2004	(3) 2004–11	(4) 2011–17	(5) 1983–2017
Dependent variable →	Panel A: change in log(employment share)				
ln wage (t – 1)	–0.146	–0.754	–1.060	–3.310***	–8.038**
	(1.854)	(1.383)	(2.338)	(1.143)	(3.813)
Sq (ln wage (t – 1))	0.020	0.040	0.077	0.208***	0.563**
	(0.126)	(0.090)	(0.146)	(0.071)	(0.261)
Constant	–0.018	3.316	3.342	13.029***	28.240**
	(6.779)	(5.309)	(9.336)	(4.611)	(13.878)
Observations	101	101	101	106	101
R-squared	0.079	0.061	0.020	0.069	0.057
Adj. R-squared	0.0607	0.0418	–8.47e–05	0.0504	0.0382
F-test	0.0470	0.276	0.351	0.0114	0.0450
Dependent variable →	Panel B: change in log(mean wage)				
ln wage (t – 1)	1.021**	–3.021***	–1.590	1.347***	–1.486*
	(0.445)	(0.725)	(1.042)	(0.395)	(0.876)
Sq (ln wage (t – 1))	–0.068**	0.215***	0.089	–0.097***	0.095
	(0.032)	(0.049)	(0.066)	(0.025)	(0.061)
Constant	–3.451**	10.737***	7.100*	–4.577***	6.509**
	(1.555)	(2.693)	(4.094)	(1.581)	(3.144)
Observations	101	101	101	106	101
R-squared	0.083	0.364	0.265	0.639	0.128
Adj. R-squared	0.0640	0.351	0.250	0.632	0.110
F-test	0.000578	1.68e–07	0.00142	0	0.0103

Note: the sample includes urban non-agricultural paid workers.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

We estimate the above equations for urban paid workers in non-agriculture due to the aforementioned reasons. Estimates for polarization in employment are given in Table 7. The results show evidence of job polarization during 2004–17. Workforce shares decrease with initial earnings and then rise (negative coefficient on log initial wage and positive coefficient on square of log initial wage).[19] However, estimates for earnings polarization do not show such a pattern during 2011–17. If anything, the effect on earnings

[19] Appendix Figure B1 also plots the changes in employment and earnings by skill percentiles captured through wages.

is in the opposite direction. Earnings polarization occurred during 1993–2011, which results in overall evidence for earnings polarization during 1983–2017, but the time period of earnings polarization does not coincide with job polarization. Hence, the period 2011–17 shows conflicting evidence—job polarization without earnings polarization—unlike the findings for the USA, where earnings polarization has accompanied job polarization. Again, in the Indian context this can reflect supply–demand mismatch in the Indian urban labour market, or institutional factors like increasing minimum wages post-2006.

3.4 Regression-based evidence: changes in employment by RTI measures

Next we look at change in employment and earnings by routine task content of jobs. We conduct a regression-based test using a quadratic specification in RTI calculated at the three-digit occupational classification using O*NET and at the two-digit level using the country-specific RTI values. The below equations are estimated for change in employment and earnings:

$$\Delta \log(E_{j,t}) = \delta_0 + \delta_1 RTI_j + \delta_2 RTI_j^2 + e_3$$

$$\Delta \log(y_{j,t}) = \alpha_0 + \alpha_1 RTI_j + \alpha_2 RTI_j^2 + e_4$$

where $\Delta E_{j,t}$ is change in employment in occupation j during the period t and $t-1$ and $\Delta \log(y_{j,t})$ is change in weekly earnings in occupation j during period t and $t-1$. Here, RTI_j is the time-invariant manual RTI in occupation j. Again, both equations are estimated by weighting each occupation j by its initial employment share to avoid that results are biased by changes in composition of small occupation groups.

Measuring the task content of occupations has been attempted for India before, and studies have looked at the intensity of routine work using the O*NET data (Sarkar 2019; Vashisht and Dubey 2019). Both of these studies classify jobs into four categories: routine manual, routine cognitive, non-routine manual, and non-routine cognitive. They find a decline in the share of routine cognitive and routine manual occupations and an increase in non-routine cognitive occupations. In this analysis, we look at the RTI of each occupation by looking at the manual task content of each occupation.[20] RTI measures are constructed in two ways: by using the task contents captured in the O*NET survey for each occupation and using country-specific measures, as discussed earlier.

The changes in employment shares based on RTI of the occupation using both O*NET RTI and country-specific measures are shown in Table 8. The results show that there has been a decline in employment share for occupations that have a higher routine task content and that these results are stronger for country-specific RTI measures at the two-digit level. In contrast, Table 9 shows that earnings have increased in occupations with the largest RTI during 2004–17. These conflicting changes by RTI also point at demand–supply mismatch across occupations in India. While demand in occupations with lower manual task content is increasing, the supply of workers has possibly outpaced the demand. Other factors affecting changes in earnings could be rising minimum wages at the lower end of the earnings spectrum and the effect of a major public works programme—the National Rural Employment Guarantee Act (NREGA)—on wages in India.

[20] The RTI is arrived at by the following formula: RTI = log((routine cognitive + routine manual)/2) – log((non-routine cognitive-analytical + non-routine cognitive-personal)/2). The measures are derived using the methodology in Autor et al. (2003) and are transformed to avoid any non-positive values in the logarithm.

Table 8: Change in employment by RTI: paid, non-agriculture, urban

	(1) 1983–93	(2) 1993–2004	(3) 2004–11	(4) 2011–17	(5) 1983–2017
Dependent variable →	Change in log(employment share)				
	Panel A: O*NET RTI (three-digit)				
O*NET RTI	–0.057*	–0.026	0.012	–0.090**	–0.098
	(0.030)	(0.034)	(0.067)	(0.036)	(0.080)
Sq (O*NET RTI)	–0.005	–0.007	0.066	0.038	0.065
	(0.016)	(0.023)	(0.042)	(0.024)	(0.056)
Constant	0.008	–0.034	–0.322***	–0.071	–0.350***
	(0.035)	(0.064)	(0.118)	(0.048)	(0.131)
Observations	101	101	101	106	101
R-squared	0.071	0.011	0.034	0.100	0.033
Adj. R-squared	0.0517	–0.00882	0.0140	0.0820	0.0130
F-test	0.116	0.726	0.161	0.0334	0.287
	Panel B: country-specific RTI (two-digit)				
CS RTI	–0.266**	0.220	–0.593**	–0.251**	–0.955***
	(0.123)	(0.161)	(0.262)	(0.092)	(0.291)
Sq (CS RTI)	0.179	–0.300	0.735**	0.314*	1.038***
	(0.150)	(0.265)	(0.290)	(0.164)	(0.321)
Constant	0.039	–0.013	–0.069	–0.041	–0.070
	(0.046)	(0.074)	(0.078)	(0.049)	(0.130)
Observations	26	26	26	26	26
R-squared	0.153	0.068	0.240	0.127	0.267
Adj. R-squared	0.0799	–0.0127	0.174	0.0509	0.203
F-test	0.0391	0.401	0.0586	0.0384	0.00882

Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at the two-digit level and O*NET RTI at the three-digit level is used.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Table 9: Change in earnings by RTI: paid, non-agriculture, urban

	(1) 1983–93	(2) 1993–2004	(3) 2004–2011	(4) 2011-2017	(5) 1983–2017
Dependent variable →	Change in log(mean wage)				
	Panel A: O*NET RTI (three-digit)				
O*NET RTI	–0.022**	–0.103***	0.065**	0.073***	0.007
	(0.010)	(0.018)	(0.028)	(0.017)	(0.025)
Sq (O*NET RTI)	–0.007	0.003	–0.005	–0.004	–0.005
	(0.004)	(0.009)	(0.015)	(0.007)	(0.012)
Constant	0.359***	0.235***	0.193***	–0.022	0.758***
	(0.013)	(0.024)	(0.046)	(0.021)	(0.032)
Observations	101	101	101	106	101
R-squared	0.082	0.307	0.076	0.259	0.003
Adj. R-squared	0.0630	0.293	0.0568	0.244	–0.0178
F-test	0.0197	4.42e–07	0.0656	1.12e–06	0.895
	Panel B: country-specific RTI (two-digit)				
CS RTI	0.030	–0.425***	0.182**	0.364***	0.158**
	(0.050)	(0.089)	(0.075)	(0.067)	(0.071)
Sq (CS RTI)	–0.134**	0.234**	–0.069	–0.211***	-0.167**
	(0.057)	(0.097)	(0.113)	(0.072)	(0.074)
Constant	0.376***	0.274***	0.147***	–0.068**	0.726***
	(0.013)	(0.035)	(0.033)	(0.025)	(0.022)
Observations	26	26	26	26	26
R-squared	0.427	0.585	0.260	0.643	0.140
Adj. R-squared	0.377	0.548	0.196	0.612	0.0654
F-test	0.00602	4.07e–05	0.00981	1.05e–05	0.0915

Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at the two-digit level and O*NET RTI at the three-digit level is used.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

3.5 Shapley decomposition

As a next step, we examine whether changes in task content of jobs over time can explain the trends in inequality. We decompose the change in earnings inequality (Gini) during every sub-period from 1983/84 to 2017/18 in our analyses, as well as over the entire time period, using Shapley decomposition. Inequality is measured using the Gini index. We decompose the changes in Gini over time into two components: contribution of changes in within-occupation inequality (i.e. among workers performing similar tasks; in other words, changes in weekly earnings inequality explained by other factors like age, education, and other sociodemographics, which are not related with the characteristics of occupation) and changes in between-occupation inequality (i.e. among workers performing different tasks; in other words, changes in average earnings across occupations). Average earnings inequality could change over time if there are composition shifts in occupational structure—for example, if there is job polarization with no change in structure of earnings, then earnings inequality could increase. Similarly, if there is no change in occupational structure but earnings structure changes such that high-paying jobs get more of the pie, then earnings inequality could again rise.

Shapley decomposition: methodology

The measure of inequality used in this decomposition is the mean log deviation in earnings (Chakravarty 2009). Let y denote individual earnings and $G(y)$ denote the Gini index. Then between-group inequality is defined by $G(y_b)$, where y_b=$(m^1,\ldots,m^J)$; that is, a vector in which the earnings of all workers in occupation $j = 1,\ldots,J$ are replaced by the average earnings in that occupation, m^j. Within-occupation inequality is defined as $G(y_w)$, where $y_w = (y^1\frac{m}{m^1},\ldots,y^J\frac{m}{m^J})$ is a vector in which the earnings of all workers are re-scaled so that all occupations have the same average earnings, m. An alternative estimate for contribution of between-group inequality is $G(y)-G(y_w)$; similarly, for contribution of within-group inequality this is $G(y)-G(y_b)$. Both of these measures are equal when, instead of Gini, the measure of inequality is taken as mean log deviation. When using Gini, however, the two are not equal. In Shapley decomposition the contribution of each term is estimated as the average of the two possible contributions, so that between-group G_B and within-group G_W contributions add up to total inequality:

$$G = G_B + G_W$$

where $G_B = 1/2[G(y_b)+G-G(y_w)]$ and $G_W = 1/2[G(y_w)+G-G(y_b)]$. This overcomes the aforementioned issues of path dependency in the calculation of contribution of within- and between-occupation inequality. This allows the change in inequality over time to be decomposed into: $\Delta G = \Delta G_B + \Delta G_W$.

Notably, between-occupation inequality can change due to two factors: change in structure of employment and change in earnings gap between occupations. To disentangle whether changes in employment structure or changes in average earnings are driving the trend in inequality between occupations, we repeat the analysis with counterfactual distributions in which either the occupational shares or the occupational mean earnings are kept constant. To understand the importance of the two channels we undertake counterfactual estimation for what would have happened to the Gini if the occupational shares were kept constant (G_{BE}) or the average earnings distribution was kept constant (G_{BM}):

$$\Delta G_B = \Delta G_{BE} + \Delta G_{BM}$$

Here, a higher contribution of ΔG_{BE} indicates that inequality between occupations is changing due to a composition effect (changes in employment shares) while a higher contribution of ΔG_{BM} indicates that change in inequality between occupations is driven by changing structure of average earnings.

We then calculate the concentration index, which enables us to understand the extent of correlation between average earnings and RTI and the overall role of changing RTI of jobs in explaining the trends in inequality. To do this we sort the occupations by their RTI instead of average earnings to construct a measure of between-occupation inequality (i.e. $G(y_b)$). The Gini index is defined as twice the area between the Lorenz curve and the 45-degree line. Similarly, the Gini concentration index is defined as twice the area between the concentration curve and the diagonal (Kakwani 1980). The Lorenz curve of the distribution of earnings between occupations plots the cumulative distribution of occupation earnings for each cumulative proportion of employment, with occupations sorted by earnings. On the other hand, the concentration curve plots the same but with workers sorted by RTI in this case (sorted from highest to lowest RTI occupations). The concentration and between-group inequality indices are the same if we get the same ranking of occupations regardless of whether they are sorted by average earnings or from highest to lowest RTI. This is likely to hold to the extent that occupations with least routine tasks have higher earnings.

Shapley decomposition: results

Table 10 shows the Shapley decomposition for urban, paid, non-agriculture workers. On average, contribution of within-occupation factors towards earnings inequality is greater. Between-occupation inequality explained 36.41 per cent of income inequality in 1983. This increased to 46 per cent in 2004, remained stable during 2004–11, and declined during 2011–17 to reach 43 per cent. Therefore, overall inequality among urban workers increased from 1983 to 2004 largely due to a rise in between-occupation inequality (0.15 in 1983 to 0.24 in 2011) rather than the rise in within-occupation inequality (0.26 in 1983 to 0.27 in 2011). Overall inequality has contracted in 2017 compared to 2011, again mostly due to a decline in between-occupation inequality (0.24 in 2011 to 0.19 in 2017). Although the bulk share is dominated by the presence of within-occupation inequality, trends are more sensitive to between-occupation inequality.

Table 10: Gini index decomposed into inequality between and within occupations: paid, non-agriculture, urban

	1983	1993	2004	2011	2017
			Panel A: actual		
1 Overall Gini	0.404	0.429	0.504	0.503	0.444
2 Between-occupation	0.147	0.174	0.233	0.235	0.193
Percentage ratio	36.41	40.68	46.16	46.77	43.53
3 Within-occupation	0.257	0.254	0.271	0.268	0.251
Percentage ratio	63.59	59.32	53.84	53.23	56.47
			Panel B: shares constant		
1 Overall Gini	0.404	0.429	0.504	0.503	0.428
2 Between-occupation	0.147	0.174	0.233	0.235	0.172
Percentage ratio	36.41	40.68	46.16	46.77	40.18
3 Within-occupation	0.257	0.254	0.271	0.268	0.256
Percentage ratio	63.59	59.32	53.84	53.23	59.82
			Panel C: means constant		
1 Overall Gini	0.404	0.413	0.450	0.465	0.449
2 Between-occupation	0.147	0.152	0.155	0.184	0.202
Percentage ratio	36.41	36.86	34.53	39.61	44.94
3 Within-occupation	0.257	0.261	0.295	0.281	0.247
Percentage ratio	63.59	63.14	65.47	60.39	55.06

Note: the sample includes urban, non-agricultural, paid workers.
Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

We further decompose the inequality in earnings between occupations into the contribution of differences in mean earnings across occupations (holding occupation shares constant in Panel B) and differences in occupation shares (holding mean earnings constant in Panel C). Holding shares constant estimates the change in inequality associated with changes in remuneration for job characteristics (e.g. skills and tasks) in the labour market, while the mean earnings constant estimates the effect on inequality of changes in employment composition (e.g. movement of workers towards higher-skilled and less routine occupations). The results show that the period of rising between-occupation inequality (1983–2011) is explained largely by a change in the structure of earnings rather than occupational shares changing—that is, due to an increasing gap in average earnings across occupations. On the other hand, results for the period of inequality decline (2011–17) show that inequality would have been lower if occupational shares were held constant (0.18 vs 0.20 actual between-occupation inequality). One of the major takeaways is that income inequality has increased due to the changes in earnings structure from 1983 to 2011 (had the earnings structure remained the same, there would have been lower inequality in 2004 than what we actually observe) and declined due to changes in employment structure from 2011 to 2017.

Overall, the above results throw up a question about whether there is any role of the tasks performed by workers and in the returns to these tasks in explaining the observed trends in between-occupation inequality. To ascertain the effect of RTI (i.e. whether the extent of manual task content of occupations is associated with changes in earnings inequality between occupations), we look at the changes in the concentration index (Table 11). We infer the extent to which the decrease in routine intensity of occupations is associated with this initial increase in earnings inequality between occupations (1983–2011) and then a decline in earnings inequality (2011–17). First, it can be noticed that the two occupation rankings are highly similar in 1983, as indicated by the corresponding concentration ratios (varies between 78 and 90 per cent for the country-specific measure and 70 and 85 per cent for the O*NET measure). With an increase in between-occupation inequality from 1983 to 2011, there is an increase in rank correlations between earnings and both measures of RTI from 0.16 in 1983 to 0.29 in 2011 for O*NET, and 0.18 in 1983 to 0.31 in 2011 for the country-specific RTI measure. With a decline in between-occupation inequality, both country-specific RTI and O*NET RTI declined. Overall, an increase in correlation using both RTI measures indicates that the relationship between routine intensity of occupations and average earnings has become stronger for the period as a whole, but there are important sub-period trends: the relation between RTI and average earnings was stronger during 1983–2011 but has declined during the most recent period of 2011–17.

Table 11: Concentration index: paid, non-agriculture, urban

	1983	1993	2004	2011	2017
			Panel A: actual		
Gini between occupations	0.232	0.268	0.347	0.346	0.286
RTI (country-specific)	0.183	0.220	0.293	0.310	0.253
Percentage ratio	78.96	82.20	84.65	89.46	88.49
RTI (O*NET)	0.164	0.212	0.280	0.293	0.243
Percentage ratio	70.83	79.13	80.87	84.68	84.96
			Panel B: shares constant		
Gini between occupations	0.232	0.268	0.347	0.346	0.259
RTI (country-specific)	0.183	0.220	0.293	0.310	0.205
Percentage ratio	78.96	82.20	84.65	89.46	79.08
RTI (O*NET)	0.164	0.212	0.280	0.293	0.197
Percentage ratio	70.83	79.13	80.87	84.68	75.92
			Panel C: means constant		
Gini between occupations	0.232	0.239	0.246	0.282	0.306
RTI (country-specific)	0.183	0.195	0.191	0.239	0.255
Percentage ratio	78.96	81.82	77.65	84.60	83.34
RTI (O*NET)	0.164	0.174	0.174	0.214	0.232
Percentage ratio	70.83	73.00	70.72	75.75	75.71

Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI is at the two-digit level and O*NET RTI it at the three-digit level.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

4 RIF-based decomposition: what drives the change in inequality?

Next, we use a RIF regression-based decomposition to further probe the role played by RTI of occupations in shaping inequality, while controlling for other competing explanations. This enables us to decompose the effect into changes in the composition of employment by occupation and other characteristics (composition effect) or in the changes in returns to characteristics (earnings structure effect).

4.1 RIF decomposition: methodology

We first present the brief methodology behind the decomposition. The methodology was developed by Firpo et al. (2007, 2009, 2018) to quantify the role played by different variables in explaining the change in inequality at different points in the earnings distribution. Unlike the previous methods, which only foretold the total change in inequality in a composition and earnings structure effect, this methodology allows one to see how much each of the covariates contribute to the composition and to the earnings structure effect. This extends the Oaxaca–Blinder decomposition since 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 rather than for average earnings. In the context of this study it allows us to quantify the extent to which changes in inequality over time can be attributed to changes in the distributions of worker characteristics and changes in the remuneration to these characteristics. The decomposition involves two steps. First, a semi-parametric propensity score is used to decompose the distributional changes between the initial and the final period into an aggregate composition effect and an aggregate earnings structure effect. Second, RIF regressions are used to further decompose the two components into the contribution by each set of explanatory variables. We discuss the details below.

Consider a general function, $v(F_y)$, that represents any distributional parameter such as the Gini index, interquantile ratio, or earnings quantile, as a function of the earnings distribution $(F_y(y))$. Consider two time periods $t = 0$ and $t = 1$. We divide the change in the distributional parameter between these time periods into two component: a *composition effect* driven by change in worker characteristics (X) and a *wage structure* effect driven by change in returns to these characteristics ($F(yX)$) over time. Let $v(F_{y_{st}})$ denote the distributional parameter when workers in year t obtain earnings under the earnings structure prevailing in year s. Using this notation, $v(F_{y_{0t=0}})$ represents the distribution parameter in $t = 0$ and $v(F_{y_{1t=1}})$ represents the distribution parameter in $t = 1$, while $v(F_{y_{0t=1}})$ represents the counterfactual distributional parameter that would have prevailed if workers in period 1 had obtained the earning given by the earning structure in period 0. This counterfactual measure is not observed and is used to decompose the change in distributional parameter in the following manner:

$$\Delta_0^v = v(F_{y_{1t=1}}) - v(F_{y_{0t=0}}) = \underbrace{[v(F_{y_{1t=1}}) - v(F_{y_{0t=1}})]}_{\Delta_s^v} + \underbrace{[v(F_{y_{0t=1}}) - v(F_{y_{0t=0}})]}_{\Delta_X^v}$$

Here, Δ_s^v is the *earnings structure* effect and Δ_X^v is the *composition effect*. The key thing here is to obtain the counterfactual distributional parameter. To do this, a reweighting function is constructed which reweights the observations in the first year such that it represents the characteristics of the final year after reweighting. The reweighting factor ($\varphi(X)$) is estimated by using the propensity score reweighting method that applies Bayes' rule in the following manner:

$$\varphi(X) = \frac{\Pr(Xt = 1)}{\Pr(Xt = 0)} = \frac{\Pr(t = 1X)\Pr(t = 0)}{\Pr(t = 0X)\Pr(t = 1)}$$

In the above reweighting function, $\Pr(t = 1X)$ can be obtained by either a logit or a probit regression in which the dependent variable is whether or not an observation belongs to year 1 based on the observed characteristics X. $\Pr(t = 0)$ simply reflects the percentage observations in year 0. Thus, the probabilities for both the numerator and the denominator can be obtained to give the final reweighting function. We use this reweighting function to reweight the observations in year 0 to give more weight to observations having characteristics similar to year 1. For instance, if the educated workforce increases in year 1 then the weight given to more educated workers in year 0 will be larger, such that the final education distribution of the workforce in year 0 matches that in year 1. We then estimate the distributional measure of interest v for this counterfactual distribution.

In the second step, we obtain the contribution of each explanatory variable to the two components. This is done using the RIF decomposition method, which is similar to the Oaxaca–Blinder approach. The only difference is that now the outcome variable, log of earnings, is replaced by the RIF of the target statistic v, $RIF(y; v)$. The RIF function is defined as:

$$RIF(y; v) = v(F) + IF(y; v)$$

Here, IF is the influence function that measures the impact on the statistic of marginally increasing the population mass at y and has an expected value of 0. Thus, the expected value of the RIF function is v. The RIFs for different distributional statistics like quantile and the Gini index have been computed (Firpo et al. 2018) and can be used directly. Next, an OLS (ordinary least squares) regression of the corresponding RIF on X is estimated for the initial and last time periods, as well as for the counterfactual:

$$RIF(y_{it}; v) = \gamma_t X_{it}$$

The above regressions are used to decompose the difference in the distributional parameter between two time periods by replacing the log of earnings with the corresponding $RIF(y_{it}; v)$ for each observation and using a suitable counterfactual. The aggregate structural effect obtained by reweighting can then be decomposed into a RIF structural effect $\Delta^v_{(S,p)}$ and a RIF reweighting error $\Delta^v_{(S,e)}$. Similarly, a second RIF decomposition can be used to decompose the composition effect into a RIF composition effect $\Delta^v_{(X,p)}$ and a specification error $\Delta^v_{(X,e)}$. Since the RIF is linear, it is then possible to obtain the detailed contribution of explanatory variables to each of the four components. The ones that will be of interest are the detailed structural effects ($\Delta^v_{(S,p)}$) and the detailed composition effects ($\Delta^v_{(X,p)}$). Standard errors are obtained after bootstrapping the entire process (reweighting and RIF decompositions) using a large number of replications (100).

4.2 RIF decomposition: results

Table 12 shows the decomposition results from RIF-based methods for change in Gini (earnings) over time. The covariates include age group, gender, education categories, religion categories, caste categories, and a quadratic in country-specific two-digit RTI.[21] The RIF decomposition analyses confirms some of the previous descriptive results. We first check whether *composition effect* or *earnings structure* is stronger for India. The results in Table 12 show that changes in the demographic characteristics (i.e. age, gender, religion, caste) and education levels of the workforce, or in the structure of employment (i.e. shift of workers towards less routine occupations), do not seem to explain the trends in inequality. The change in structure of earnings across occupations explains the inequality trends observed: increase between 1983 and 2004 and a subsequent decline during 2011–17. The decomposition effects are plotted for each quantile in Figure 7 for the entire period and in Figure 8 for each sub-period. The contribution of each type of effect does not vary much by quantile and sub-period, and the earnings structure effect dominates. This warrants a detailed look at what factors contribute towards the change in structure of earnings.

Table 12: Decomposition of the change in Gini: RIF regression using country-specific RTI at the two-digit level (paid, non-agriculture, urban)

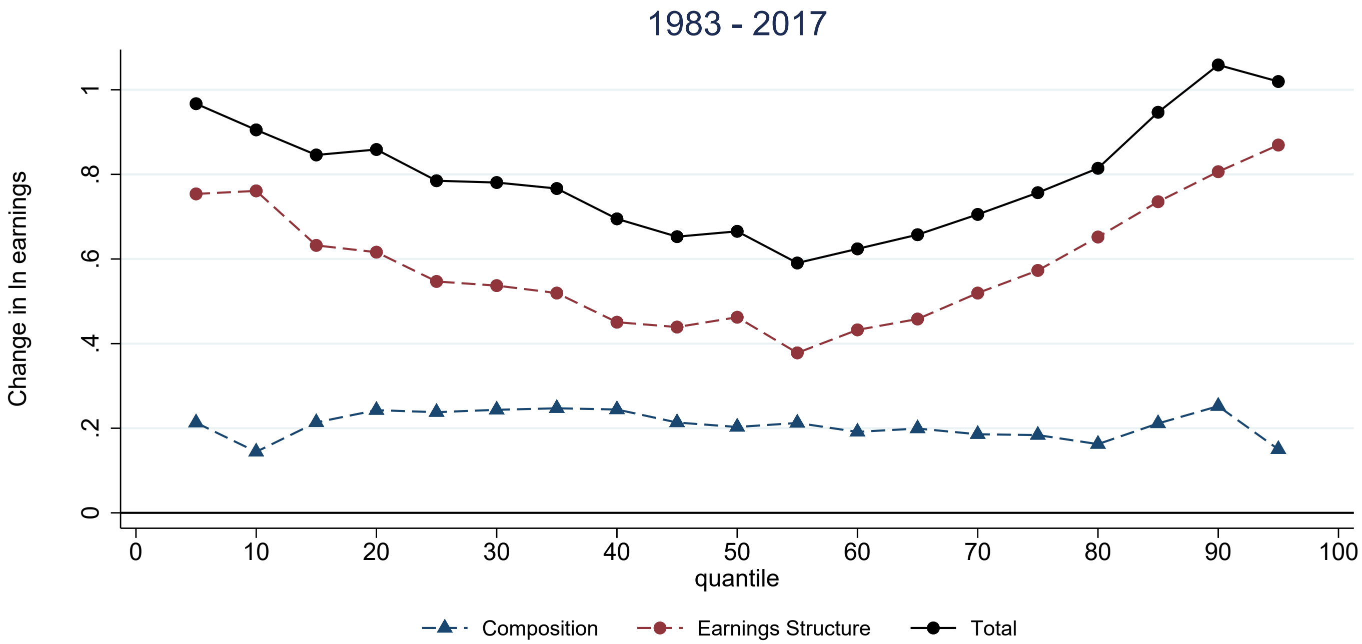
	1983–2017		1983–93		1993–2004		2004–11		2011–17	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Change	0.044	0.005	0.028	0.004	0.076	0.004	–0.001	0.005	–0.059	0.004
Reweighting										
Composition	–0.008	0.003	0.000	0.002	0.003	0.002	–0.001	0.002	0.002	0.001
Earnings structure	0.052	0.004	0.028	0.004	0.073	0.005	0.000	0.005	–0.061	0.004
RIF										
Composition	0.015	0.003	0.000	0.001	0.002	0.001	0.005	0.002	0.005	0.001
Specification error	–0.023	0.002	0.000	0.001	0.001	0.001	–0.006	0.001	–0.003	0.001
Earnings structure	0.054	0.004	0.028	0.004	0.074	0.005	–0.001	0.005	–0.061	0.004
Re–weighting error	–0.002	0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
Detailed earnings structure										
Age	0.008	0.004	–0.002	0.003	–0.011	0.004	0.004	0.005	0.014	0.003
Sex	0.009	0.002	0.002	0.001	–0.005	0.002	0.002	0.002	0.007	0.002
Education	0.045	0.008	0.001	0.005	0.003	0.005	0.011	0.006	0.030	0.006
Religion	0.004	0.002	0.005	0.001	–0.001	0.002	–0.001	0.002	0.001	0.002
Social group	0.011	0.002	0.003	0.001	0.002	0.002	0.001	0.002	0.007	0.002
RTI	–0.026	0.005	–0.004	0.004	–0.024	0.005	–0.010	0.004	–0.006	0.003
Intercept	0.003	0.011	0.023	0.009	0.110	0.015	–0.008	0.014	–0.113	0.011

Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at the two-digit level is used to control for RTI of an occupation.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

[21] We also check the robustness of the results using O*NET-based RTI measures and find that they do not differ much. A detailed look at the RIF decompositions shows that while the reweighting error is small across specifications, the specification errors can be large in some specifications, especially for the whole period 1983–2017.

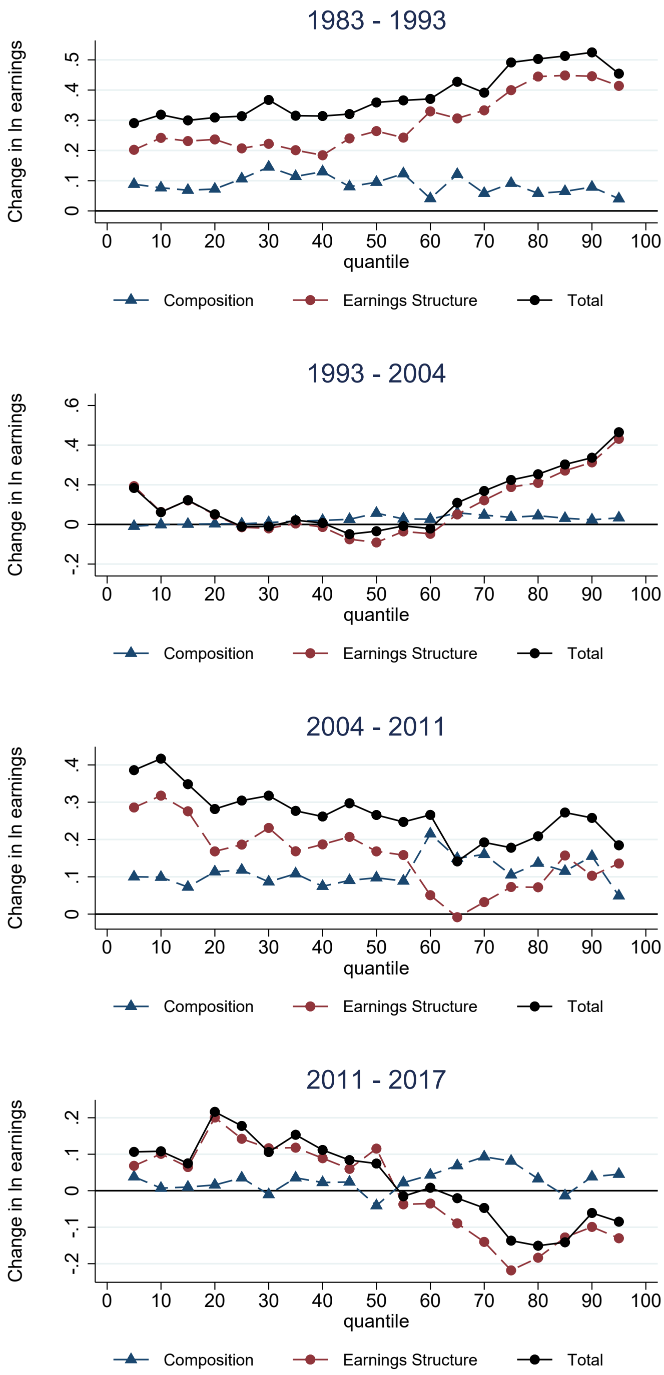
Figure 7: Decomposition of the change in Gini by quantile (1983–2017)



Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at the two-digit level is used to control for RTI of an occupation.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Figure 8: Decomposition of the change in Gini by quantile (by sub-period)

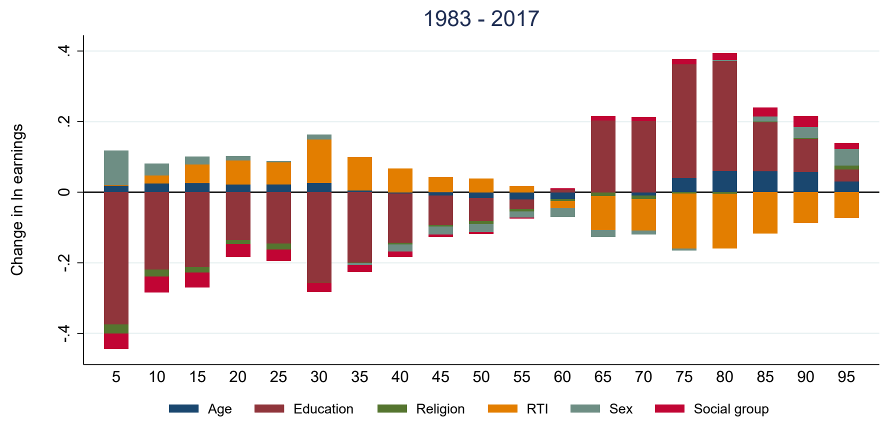


Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at the two-digit level is used to control for RTI of an occupation.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Figure 9 shows the detailed *earnings structure* effect for the entire period, while Figure 10 shows it for each sub-period. The figures plot the component of the earnings structure that can be explained by the factors included in the regression analyses. The total earnings structure effect is composed of three components: the explained portion, an intercept, and an error. Therefore, if the intercept and the error components are large or in the opposite direction (for instance, in the sub-period 2004–17), the total earnings structure in Figure 8 will not be equal to the explained component displayed in Figure 10. The detailed effects are plotted for each quantile to see how much of the change in earnings for that quantile is explained by the changing structure of earnings over time for each explanatory variable. The results in Figure 9 show that changes in returns to education and changes in returns to RTI have contributed the most to the change in earnings structure across all quantiles. The direction for the two is, however, opposite. While changes in the returns to education contribute positively to the increased earnings at the upper quantiles, they result in decreased earnings at the lower quantiles. This shows that change in returns to education have had a dis-equalizing effect on earnings in India. This is in line with the findings that between 1983 and 2017, education premiums have increased in India. On the other hand, changes in return to RTI have resulted in lower earnings at the upper end and higher earnings in the lower quantiles. This shows that change in returns to RTI have had an equalizing effect on earnings in India. Therefore, controlling for other factors, changes in returns to routine tasks in jobs would have led to a decline in inequality in India.

Figure 9: **Detailed decomposition of the change in Gini by quantile for earnings structure (1983–2017)**



Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at the two-digit level is used to control for RTI of an occupation.

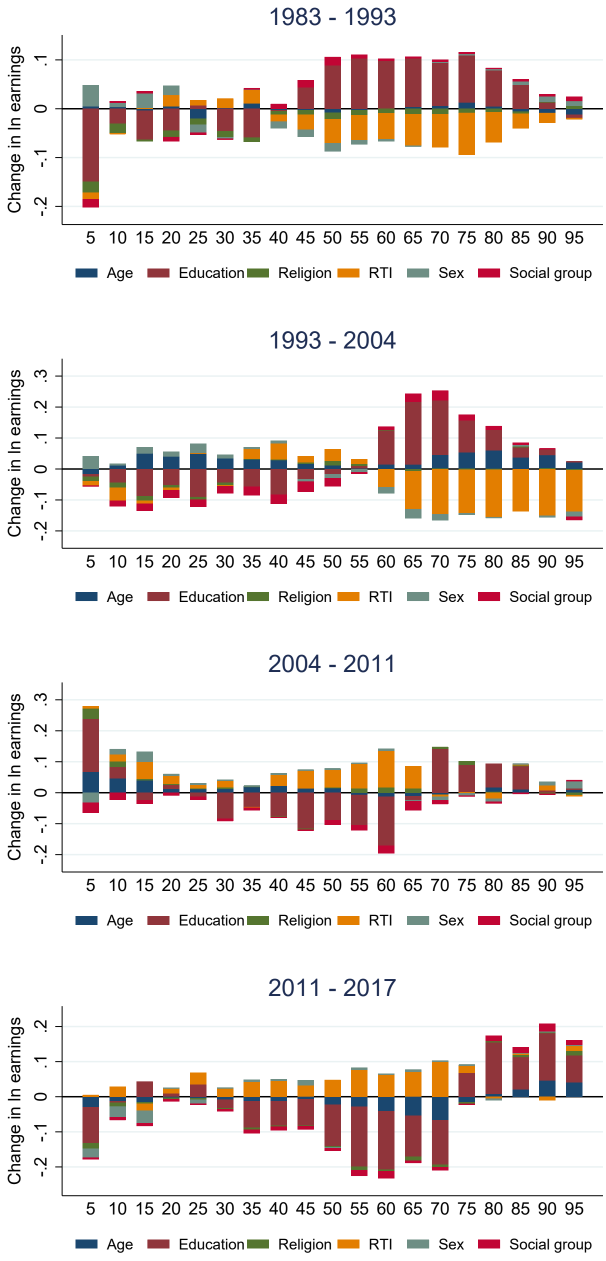
Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

In line with our previous findings, the sub-period graphs also show that changes in returns to education have a dis-equalizing effect in each sub-period which is stronger during 1983–2004. Post-2004, returns to education contribute positively to the earnings of the bottom quartile, resulting in an equalizing effect at the lower end of the earnings distribution and in a dis-equalizing effect at the upper end of the earnings distribution. The only notable difference in the effect of education on wage inequality is during 2004–17. This is in line with falling education premiums but largely with respect to the illiterate category of workers. The overall rising/stable education premiums across other category of workers reflect the effect of education earnings structure in the upper-middle part of the distribution. Changes in returns to RTI increase the wages in the middle part of the distribution and therefore continue to have an equalizing effect.

We check the robustness of the above results to including controls for the industry (sector of work) structure. Table B3 shows the results with the additional controls. Even after controlling for these, the composition effect remains small and the earnings structure effect is the major driver in explaining the changes in inequality in each sub-period. The analysis by quantile is shown in Figures B2 and B3. The detailed earnings structure effect by quantile is shown in Figures B4 and B5. The detailed analysis of the earnings structure effect shows that the contribution of changes in returns to education and changes in returns to RTI in explaining overall change in earnings at each quantile do not change much. The change in returns to industry have an equalizing effect on wages. We also check the robustness of the main decomposition results using the country-specific measure of RTI at the three-digit level in Table B4 and find that the previous findings hold. Last, we change the measure of inequality to the interquantile range of log of earnings in Table B5. The results here show that the largest decline in wage inequality has occurred in the upper end (q90–q50). The inequality at the lower end (q50–q10) declines during

1993–2004, but did not change during 2011–17, the period of the largest wage inequality decline. The previous finding, that the earnings structure effect dominates in explaining the changes in inequality, still holds.[22]

Figure 10: Detailed decomposition of the change in Gini by quantile for earnings structure (by sub-period)



Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at the two-digit level is used to control for RTI of an occupation.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

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[22] The detailed earnings structure for each quantile is also shown in Appendix Table B6.

5 Conclusion

We use data on employment and unemployment rounds for the last three decades to examine the trends in wage earnings inequality for paid urban workers in non-agriculture sectors. We find that there was an increase in earnings inequality in India during 1983–2004, and thereafter a strong decline in earnings inequality during 2011–17, a finding hitherto unexplored for India. Can the trends in inequality be explained by the changing occupational structure in India? We find evidence for job polarization in urban India post-2004 driven by the rise in employment share of IT services and other managerial jobs at the upper end, and of construction and services like retail at the lower end. There is, however, little evidence for earnings polarization, unlike the developed countries, and if anything there is an increase in earnings at the lower end and a decline in real earnings at the upper end of the wage distribution post-2011. In general, wage earnings are determined by both demand and supply factors. In developing countries, such as India, it is possible that the increase in supply of an educated workforce at the upper end outstripped the increase in demand for these workers, resulting in lower wage growth at the upper end. On the other hand, higher earnings growth in occupations with lower initial wages could also be due to domestic policies of rising minimum wages, especially post-2004 and rural public employment guarantee programmes (with spillover effects on urban wages) which picked pace post-2006.

We also evaluate the role of changing RTI of occupations in contributing towards the inequality changes. There is an inverted U-shape relation between earnings and RTI post-2011 which shows the changing structure of earnings post-2011 that may have been equalizing for wages. The decomposition analyses confirm these findings while controlling for other factors. The results show that the trends in inequality can be attributed to changing earnings structure rather than changes in composition of the workforce (age, gender, education, and RTI). Within the earnings structure, changes in returns to education had a dis-equalizing effect, while changes in returns to RTI had an equalizing effect on earnings inequality. Notably, a large part of change in earnings inequality remains unexplained in the model, which shows that the changes in RTI and returns to education have had a modest overall impact in shaping it. Domestic policies on minimum wages and demand–supply mismatch in skills seem to be more important in the Indian context.

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Appendix

A Imputation of earnings for urban self-employed

The NSS for 1983, 1993, 2004, and 2011 do not provide earnings for self-employed workers. We impute the weekly earnings for self-employed workers using the data for paid workers and also using the difference in the earnings gap between paid and self-employed workers. This exercise is done for urban India, where the levels of self-employment are lower (approximately 40 per cent) than in rural India (70 per cent self-employed and largely agriculture-based). The earnings are deflated for each individual at their real value in 2017 using appropriate deflators as discussed earlier. We first estimate an earnings regression for paid and self-employed workers in 2017 since the PLFS provides data on weekly earnings for both groups of workers. The below regression is estimated using the PLFS data of 2017 for men and women separately:

$$\ln(y_i) = \beta_0 + X\beta_1 + D_{SE}\delta_1 + D_{SE} * X\delta_2 + \varepsilon$$

Here, y_i is weekly earnings for individual i, X contains the individual characteristics of age, education, marital status, occupation (one digit), and resident state. D_{SE} is the indicator variable for whether or not the individual is self-employed and $D_{SE} * X$ are the interactions of the indicator variables with the individual characteristics. The indicators variable captures any aggregate differences in earnings between self-employed and paid workers, and the interactions with X capture whether the differences change with characteristics. As a first check we conduct an F-test to check the joint significance of δ_1 and δ_2 for men and women. Our results show statistically significant values of δ.

Next, we estimate the earnings for paid workers in each of the years separately—1983, 1993, 2004, and 2011—using the regression:

$$\ln(y_{it,paid}) = \gamma_{0,t} + X_t\gamma_{1,t} + e_t$$

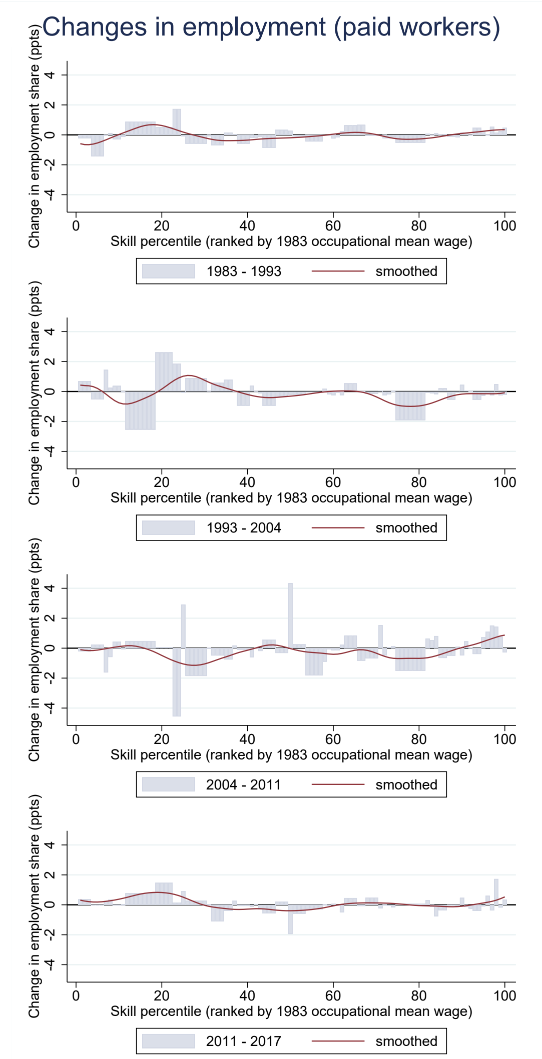
We the predict the weekly earnings for the self-employed in that year using the coefficient for paid workers from the above regressions, adjusted for the differential structure of earnings for self-employed (captured through δ):

$$\widehat{\ln(y_{it,SE})} = \widehat{\gamma_{0,t}} + X_t\widehat{\gamma_{1,t}} + \widehat{\delta_1} + X\widehat{\delta_2}$$

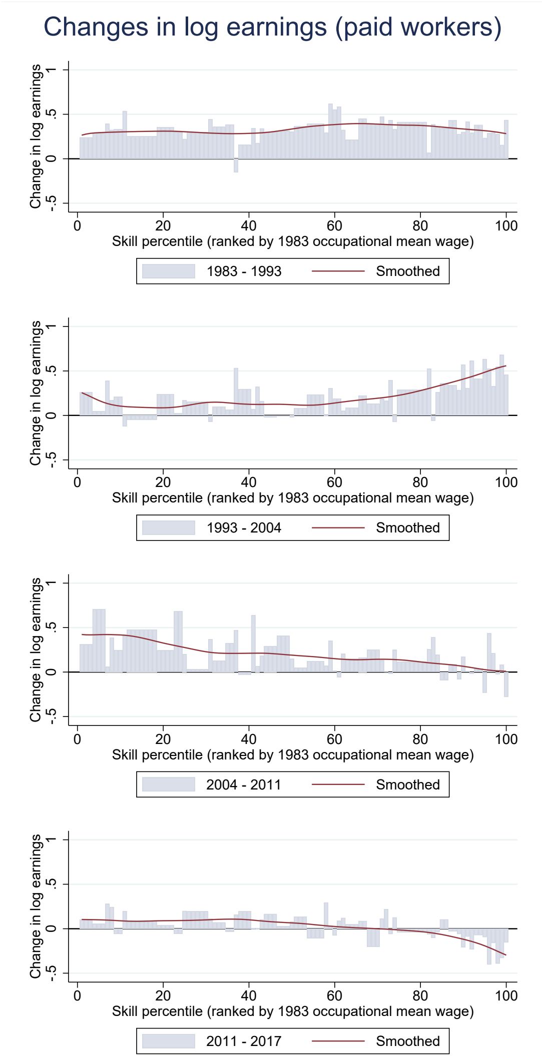
B Appendix figures and tables

Figure B1: Changes in employment and earnings across skill percentiles (at the two-digit level): urban, paid, non-agricultural sector

(a) Changes in employment



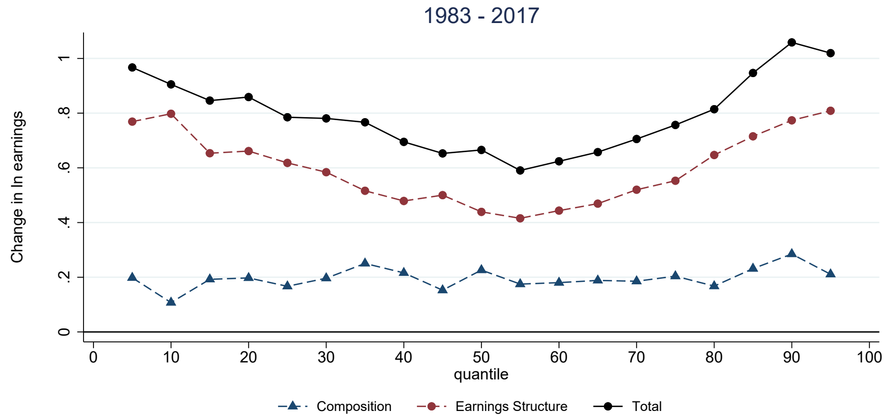
(b) Changes in earnings



Note: the sample includes urban, non-agricultural, paid workers.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

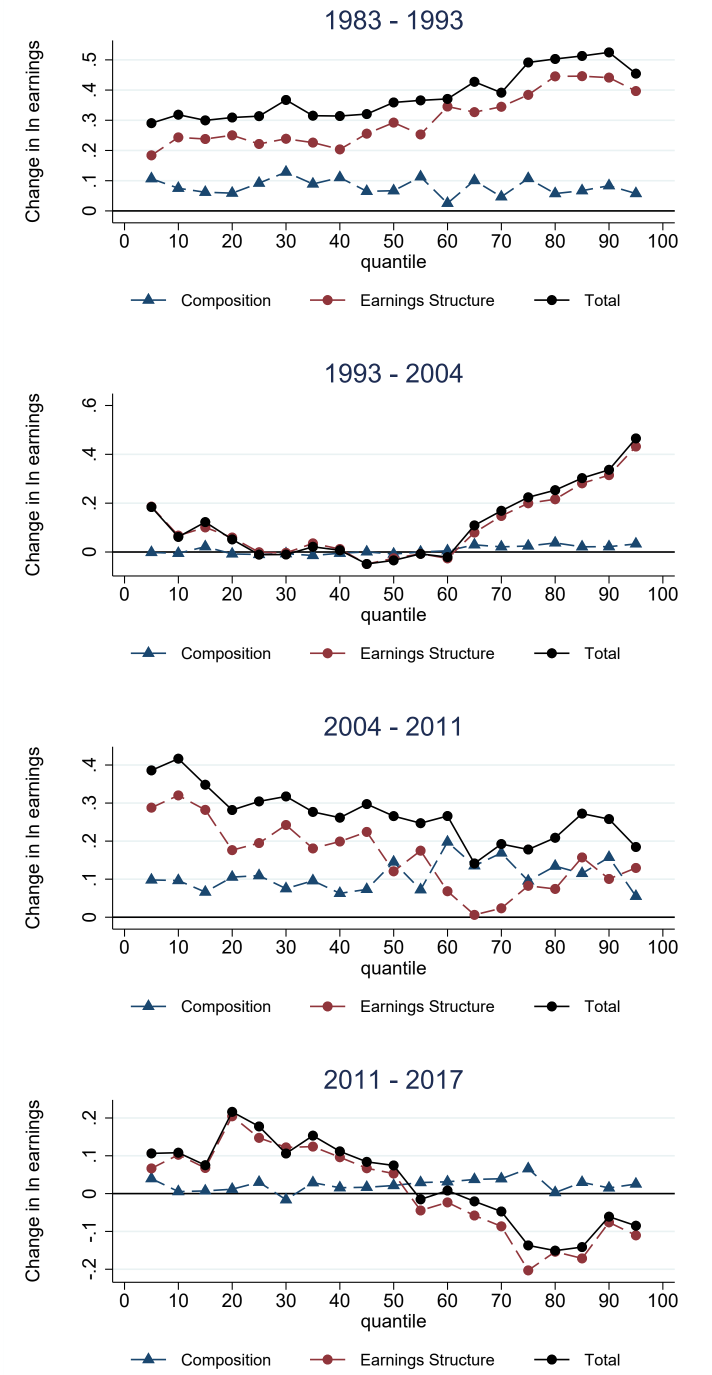
Figure B2: Decomposition of the change in Gini: by quantile (1983–2017) including additional controls for industry



Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at two-digit level is used to control for RTI of an occupation.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

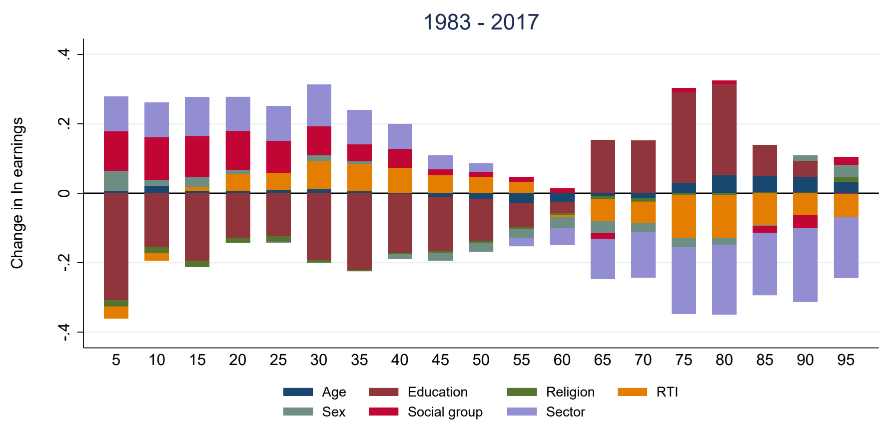
Figure B3: Decomposition of the change in Gini: by quantile (by sub-period) including additional controls for industry



Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at two-digit level is used to control for RTI of an occupation.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

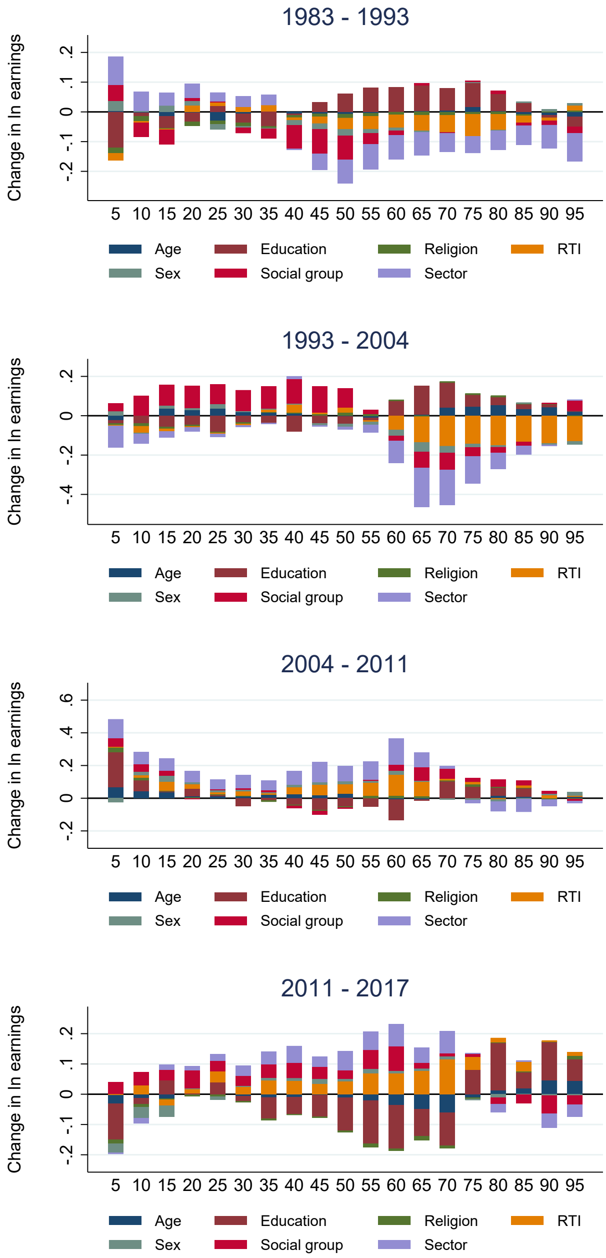
Figure B4: Detailed decomposition of the change in Gini by quantile for earnings structure (1983–2017): additional controls for industry



Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at two-digit level is used to control for RTI of an occupation.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Figure B5: Detailed decomposition of the change in Gini by quantile for earnings structure (by sub-period): additional controls for industry



Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at two-digit level is used to control for RTI of an occupation.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Table B1: Change in employment and earnings by RTI: country-specific RTI at the three-digit level, paid, non-agriculture, urban

	(1) 1983–93	(2) 1993–2004	(3) 2004–11	(4) 2011–17	(5) 1983–2017
Dependent variable →	Change in log(employment share)				
CS RTI	–0.117	0.011	0.013	–0.291***	–0.205
	(0.100)	(0.119)	(0.179)	(0.098)	(0.247)
Sq (CS RTI)	0.017	0.012	0.213	0.184***	0.273
	(0.060)	(0.063)	(0.154)	(0.063)	(0.208)
Constant	0.018	–0.068	–0.339***	–0.018	–0.352***
	(0.038)	(0.052)	(0.118)	(0.041)	(0.118)
Observations	101	101	101	106	101
R-squared	0.045	0.002	0.061	0.127	0.043
Adj. R-squared	0.0251	–0.0185	0.0415	0.110	0.0230
F-test	0.175	0.942	0.104	0.00906	0.421
Dependent variable →	Change in log(mean wage)				
CS RTI	–0.033	–0.299***	0.187**	0.227***	0.057
	(0.036)	(0.057)	(0.084)	(0.051)	(0.071)
Sq (CS RTI)	–0.010	0.120***	–0.089	–0.066**	–0.039
	(0.025)	(0.034)	(0.061)	(0.029)	(0.046)
Constant	0.358***	0.268***	0.172***	–0.068***	0.747***
	(0.015)	(0.025)	(0.050)	(0.023)	(0.033)
Observations	101	101	101	106	101
R-squared	0.052	0.260	0.065	0.337	0.009
Adj. R-squared	0.0326	0.245	0.0458	0.324	–0.0109
F-test	0.192	0.000	0.080	0.000	0.684

Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at three-digit level is used to control for RTI of an occupation.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Table B2: Change in average RTI over time by Location

	Paid workers in all sectors			Paid workers in non-agricultural sectors
Year	All sectors	Rural sector	Urban sector	Urban sector
Panel A: O*NET RTI				
1983	0.56	0.56	0.55	0.55
1993	0.53	0.56	0.48	0.48
2004	0.55	0.59	0.45	0.45
2011	0.69	0.78	0.51	0.51
2017	0.64	0.76	0.43	0.43
Panel B: country-specific RTI				
1983	0.80	0.91	0.50	0.46
1993	0.78	0.90	0.48	0.43
2004	0.74	0.86	0.46	0.44
2011	0.70	0.84	0.43	0.41
2017	0.64	0.77	0.42	0.40

Note: country-specific RTI at two-digit level and O*NET RTI at three-digit level is used.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Table B3: Decomposition of the change in Gini: RIF regression using country-specific RTI at two-digit level and additional controls

	1983–2017		1983–93		1993–2004		2004–11		2011–17	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Change	0.044	0.005	0.028	0.004	0.076	0.005	–0.001	0.005	–0.059	0.004
Reweighting										
Composition	0.007	0.003	0.004	0.002	0.006	0.002	0.001	0.002	0.002	0.002
Earnings structure	0.037	0.005	0.024	0.004	0.070	0.005	–0.002	0.006	–0.061	0.004
RIF										
Composition	0.029	0.003	0.004	0.001	0.005	0.001	0.007	0.002	0.005	0.002
Specification error	–0.022	0.002	0.000	0.001	0.001	0.001	–0.006	0.001	–0.003	0.001
Earnings structure	0.038	0.005	0.024	0.004	0.070	0.005	–0.003	0.006	–0.061	0.004
Reweighting error	0.000	0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.000	0.000
Detailed earnings structure										
Age	0.008	0.004	–0.001	0.003	–0.008	0.004	0.003	0.004	0.014	0.004
Sex	0.006	0.002	0.001	0.001	–0.004	0.002	0.001	0.002	0.005	0.002
Education	0.037	0.009	–0.006	0.007	0.002	0.005	0.006	0.006	0.025	0.006
Religion	0.004	0.002	0.004	0.002	–0.001	0.001	0.000	0.002	0.001	0.002
Social group	–0.021	0.011	–0.004	0.007	–0.010	0.006	0.003	0.006	–0.026	0.006
RTI	–0.022	0.005	–0.003	0.005	–0.021	0.006	–0.010	0.004	–0.005	0.003
Industry	–0.058	0.005	–0.026	0.004	0.004	0.004	–0.014	0.006	–0.023	0.005
Intercept	0.083	0.016	0.058	0.013	0.108	0.019	0.008	0.017	–0.051	0.013

Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at two-digit level is used to control for RTI of an occupation.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Table B4: Decomposition of the change in Gini: RIF regression using country-specific RTI at three-digit level

	1983–2017		1983–93		1993–2004		2004–11		2011–17	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Change	0.044	0.004	0.028	0.004	0.076	0.005	–0.001	0.005	–0.059	0.004
Reweighting										
Composition	–0.010	0.003	0.000	0.002	0.006	0.002	–0.009	0.002	0.003	0.001
Earnings structure	0.054	0.004	0.028	0.004	0.070	0.005	0.008	0.005	–0.061	0.005
RIF										
Composition	0.018	0.003	0.001	0.002	0.006	0.001	–0.002	0.002	0.007	0.001
Specification error	–0.028	0.002	0.000	0.001	0.001	0.001	–0.007	0.001	–0.004	0.001
Earnings structure	0.058	0.004	0.028	0.004	0.070	0.005	0.007	0.005	–0.061	0.005
Reweighting error	–0.004	0.000	0.000	0.001	–0.001	0.000	0.000	0.000	0.000	0.000
Detailed earnings structure										
Age	0.007	0.004	–0.001	0.004	–0.010	0.004	0.001	0.004	0.014	0.004
Sex	0.008	0.002	0.002	0.001	–0.003	0.002	0.002	0.002	0.006	0.002
Education	0.055	0.007	–0.001	0.006	0.016	0.005	0.003	0.007	0.024	0.006
Religion	0.003	0.002	0.004	0.001	–0.001	0.001	–0.001	0.002	0.001	0.002
Social group	0.012	0.002	0.003	0.002	0.002	0.001	0.002	0.002	0.007	0.001
RTI	–0.012	0.004	–0.006	0.005	–0.013	0.007	–0.012	0.008	0.002	0.003
Intercept	–0.016	0.011	0.028	0.012	0.080	0.017	0.012	0.019	–0.115	0.011

Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at three-digit level is used to control for RTI of an occupation.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Table B5: Decomposition of the change in interquartile range (log earnings): RIF regression using country-specific RTI at two-digit level

	q90–q10				
	1983–2017	1983–93	1993–2004	2004–11	2011–17
Change	0.15	0.26	0.13	–0.15	–0.14
Reweighting					
Composition	0.16	0.00	–0.04	0.17	0.04
Earnings structure	–0.01	0.26	0.16	–0.32	–0.18
RIF					
Composition	0.26	0.03	0.02	0.10	0.06
Specification error	–0.10	–0.04	–0.06	0.07	–0.01
Earnings structure	0.02	0.26	0.17	–0.32	–0.18
Reweighting error	–0.03	0.00	–0.01	0.00	0.00
Detailed earnings structure					
Age	0.05	0.02	0.02	–0.04	0.06
Sex	–0.02	0.04	–0.08	–0.02	0.04
Education	0.10	0.04	0.16	–0.01	0.11
Religion	0.02	0.01	0.01	–0.02	0.01
Social group	0.04	0.01	0.01	0.02	0.04
RTI	–1.07	–0.02	–0.16	–0.07	–0.03
Intercept	3.08	0.16	0.22	–0.17	–0.42
	q90–q50				
Change	0.39	0.17	0.36	–0.01	–0.14
Reweighting					
Composition	0.04	–0.02	0.04	0.00	0.02
Earnings structure	0.36	0.19	0.32	–0.01	–0.16
RIF					
Composition	0.16	–0.01	–0.02	0.03	0.02
Specification error	–0.12	0.00	0.05	–0.03	0.00
Earnings structure	0.37	0.19	0.32	–0.02	–0.16
Reweighting error	–0.01	0.00	0.00	0.00	0.00
Detailed earnings structure					
Age	0.08	0.01	0.04	–0.02	0.06
Sex	0.02	0.03	0.01	0.00	0.00
Education	0.12	–0.02	0.08	0.11	0.25
Religion	0.01	0.01	–0.01	0.00	0.01
Social group	0.02	–0.01	0.03	0.00	0.03
RTI	–0.53	0.04	–0.23	–0.06	–0.06
Intercept	1.25	0.12	0.40	–0.04	–0.44

(Continues ...)

Table B5 (continued)

	q50–q10				
	1983–2017	1983–93	1993–2004	2004–11	2011–17
Change	–0.24	0.08	–0.23	–0.14	0.00
Reweighting					
Composition	0.12	0.02	–0.08	0.17	0.03
Earnings structure	–0.36	0.07	–0.15	–0.31	–0.03
RIF					
Composition	0.10	0.05	0.03	0.07	0.03
Specification error	0.02	–0.03	–0.11	0.10	–0.01
Earnings structure	–0.35	0.07	–0.15	–0.31	–0.03
Reweighting error	–0.02	0.00	0.00	0.00	0.00
Detailed earnings structure					
Age	–0.03	0.01	–0.02	–0.02	0.00
Sex	–0.05	0.01	–0.09	–0.02	0.04
Education	–0.02	0.06	0.08	–0.12	–0.14
Religion	0.01	0.00	0.02	–0.02	0.00
Social group	0.02	0.02	–0.02	0.01	0.01
RTI	–0.54	–0.06	0.06	–0.02	0.03
Intercept	1.83	0.04	–0.18	–0.13	0.02

Note: the sample includes urban, non-agricultural, paid workers. Country-specific RTI at two-digit level is used to control for RTI of an occupation. Period-specific quantiles are utilized.
Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Table B6: Decomposition of the change in quantiles of earnings (log): RIF regression using country-specific RTI at two-digit level

1983–2017	q5	q10	q15	q20	q25	q30	q35	q40	q45	q50	q55	q60	q65	q70	q75	q80	q85	q90	q95
Change	0.967	0.905	0.846	0.859	0.785	0.781	0.767	0.695	0.653	0.665	0.591	0.624	0.657	0.705	0.757	0.814	0.947	1.059	1.020
	(0.039)	(0.022)	(0.030)	(0.012)	(0.026)	(0.017)	(0.022)	(0.027)	(0.031)	(0.012)	(0.026)	(0.015)	(0.031)	(0.016)	(0.031)	(0.022)	(0.028)	(0.021)	(0.018)
Reweighting																			
Composition	0.080	0.096	0.145	0.157	0.163	0.185	0.210	0.243	0.230	0.226	0.217	0.205	0.215	0.229	0.226	0.230	0.234	0.266	0.349
	(0.013)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.014)	(0.012)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.012)	(0.015)	(0.020)
Specification error	0.137	0.054	0.066	0.091	0.080	0.075	0.049	0.006	–0.005	–0.016	0.006	–0.008	–0.014	–0.039	–0.027	–0.066	–0.018	–0.009	–0.194
	(0.022)	(0.027)	(0.012)	(0.011)	(0.016)	(0.019)	(0.026)	(0.015)	(0.019)	(0.018)	(0.010)	(0.014)	(0.008)	(0.009)	(0.012)	(0.009)	(0.012)	(0.022)	(0.020)
Earnings structure	0.736	0.740	0.623	0.603	0.534	0.511	0.499	0.440	0.424	0.452	0.365	0.425	0.455	0.513	0.555	0.648	0.728	0.799	0.862
	(0.042)	(0.030)	(0.032)	(0.018)	(0.026)	(0.024)	(0.020)	(0.018)	(0.027)	(0.015)	(0.020)	(0.008)	(0.025)	(0.010)	(0.029)	(0.019)	(0.029)	(0.022)	(0.022)
Reweighting error	0.015	0.015	0.012	0.009	0.008	0.009	0.008	0.006	0.004	0.003	0.003	0.002	0.002	0.003	0.003	0.002	0.002	0.003	0.002
	(0.005)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.003)
Detailed earnings structure																			
Age	0.017	0.026	0.026	0.022	0.023	0.026	0.005	–0.004	–0.010	–0.017	–0.021	–0.019	–0.002	–0.009	0.039	0.061	0.060	0.057	0.032
	(0.023)	(0.016)	(0.016)	(0.011)	(0.011)	(0.011)	(0.009)	(0.008)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.011)	(0.011)	(0.012)	(0.013)	(0.016)
Sex	0.097	0.034	0.023	0.014	0.002	0.011	–0.007	–0.021	–0.023	–0.023	–0.020	–0.025	–0.019	–0.011	–0.006	0.001	0.014	0.032	0.048
	(0.040)	(0.019)	(0.016)	(0.011)	(0.010)	(0.010)	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.009)	(0.009)	(0.009)	(0.010)	(0.012)
Education	–0.378	–0.216	–0.209	–0.137	–0.146	–0.247	–0.192	–0.142	–0.085	–0.067	–0.028	0.010	0.210	0.203	0.318	0.315	0.137	0.093	0.031
	(0.094)	(0.060)	(0.058)	(0.049)	(0.046)	(0.044)	(0.032)	(0.031)	(0.025)	(0.024)	(0.026)	(0.026)	(0.032)	(0.027)	(0.046)	(0.029)	(0.027)	(0.021)	(0.023)
Religion	–0.027	–0.021	–0.017	–0.012	–0.017	–0.002	–0.001	–0.004	–0.005	–0.008	–0.007	–0.006	–0.011	–0.010	–0.005	–0.005	0.000	0.001	0.010
	(0.012)	(0.007)	(0.007)	(0.008)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.008)	(0.009)
Social group	0.173	0.209	0.192	0.177	0.156	0.118	0.086	0.066	0.030	0.022	0.017	0.013	–0.020	–0.011	–0.010	–0.016	–0.051	–0.095	–0.047
	(0.070)	(0.046)	(0.043)	(0.032)	(0.030)	(0.035)	(0.031)	(0.027)	(0.024)	(0.024)	(0.024)	(0.021)	(0.023)	(0.022)	(0.026)	(0.028)	(0.024)	(0.027)	(0.029)
RTI	0.000	0.023	0.056	0.070	0.064	0.120	0.089	0.067	0.041	0.038	0.012	–0.021	–0.096	–0.089	–0.155	–0.154	–0.118	–0.087	–0.076
	(0.039)	(0.026)	(0.025)	(0.027)	(0.028)	(0.029)	(0.022)	(0.021)	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)	(0.021)	(0.018)	(0.016)	(0.016)	(0.019)
Intercept	0.854	0.684	0.551	0.470	0.451	0.486	0.519	0.477	0.474	0.506	0.411	0.473	0.394	0.438	0.373	0.446	0.686	0.799	0.864
	(0.136)	(0.085)	(0.080)	(0.063)	(0.066)	(0.074)	(0.068)	(0.053)	(0.042)	(0.043)	(0.044)	(0.041)	(0.049)	(0.040)	(0.065)	(0.057)	(0.060)	(0.051)	(0.056)

(Continues...)

Table B6 (continued)

1983–93	q5	q10	q15	q20	q25	q30	q35	q40	q45	q50	q55	q60	q65	q70	q75	q80	q85	q90	q95
Change	0.291	0.318	0.300	0.309	0.314	0.367	0.315	0.314	0.321	0.359	0.366	0.371	0.427	0.391	0.492	0.503	0.513	0.525	0.454
	(0.029)	(0.021)	(0.021)	(0.012)	(0.020)	(0.018)	(0.027)	(0.022)	(0.027)	(0.029)	(0.020)	(0.020)	(0.017)	(0.017)	(0.017)	(0.021)	(0.010)	(0.020)	(0.016)
Reweighting																			
Composition	0.046	0.049	0.069	0.071	0.072	0.079	0.090	0.101	0.096	0.093	0.088	0.083	0.084	0.087	0.084	0.083	0.081	0.087	0.107
	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.009)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.011)
Specification error	0.043	0.028	0.000	0.002	0.035	0.066	0.025	0.029	–0.015	0.002	0.036	–0.042	0.037	–0.028	0.010	–0.026	–0.015	–0.008	–0.066
	(0.024)	(0.023)	(0.013)	(0.019)	(0.010)	(0.008)	(0.022)	(0.014)	(0.022)	(0.014)	(0.013)	(0.013)	(0.010)	(0.007)	(0.008)	(0.008)	(0.006)	(0.014)	(0.010)
Earnings structure	0.202	0.242	0.231	0.237	0.207	0.222	0.202	0.185	0.241	0.265	0.243	0.331	0.307	0.334	0.399	0.447	0.448	0.447	0.416
	(0.044)	(0.020)	(0.018)	(0.019)	(0.012)	(0.012)	(0.018)	(0.012)	(0.026)	(0.023)	(0.016)	(0.016)	(0.015)	(0.018)	(0.017)	(0.018)	(0.012)	(0.011)	(0.020)
Reweighting error	0.000	0.000	0.000	0.000	0.000	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.001	–0.002	–0.002	–0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Detailed earnings structure																			
Age	0.005	0.003	–0.004	0.005	–0.020	0.002	0.011	–0.003	–0.003	–0.009	–0.003	0.000	0.004	0.006	0.013	0.004	–0.005	–0.008	–0.012
	(0.024)	(0.013)	(0.016)	(0.012)	(0.012)	(0.011)	(0.011)	(0.010)	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.009)	(0.014)
Sex	0.043	0.009	0.030	0.019	–0.015	–0.003	0.000	–0.014	–0.015	–0.017	–0.009	–0.005	–0.001	0.001	0.002	0.003	0.007	0.011	0.010
	(0.025)	(0.013)	(0.013)	(0.010)	(0.008)	(0.007)	(0.006)	(0.005)	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.007)
Education	–0.149	–0.030	–0.059	–0.044	0.007	–0.046	–0.058	–0.002	0.044	0.089	0.103	0.098	0.099	0.089	0.097	0.075	0.048	0.013	–0.007
	(0.068)	(0.037)	(0.047)	(0.037)	(0.030)	(0.026)	(0.029)	(0.027)	(0.026)	(0.021)	(0.021)	(0.018)	(0.017)	(0.016)	(0.015)	(0.015)	(0.017)	(0.014)	(0.016)
Religion	–0.022	–0.020	–0.003	–0.013	–0.013	–0.012	–0.009	–0.007	–0.009	–0.012	–0.010	–0.009	–0.011	–0.012	–0.008	–0.007	–0.005	0.002	0.006
	(0.012)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.004)	(0.005)	(0.007)
Social group	0.079	–0.022	–0.011	0.035	0.025	0.011	–0.013	–0.062	–0.076	–0.092	–0.039	–0.021	–0.002	–0.009	–0.002	0.001	–0.021	–0.032	–0.043
	(0.075)	(0.044)	(0.049)	(0.038)	(0.036)	(0.031)	(0.032)	(0.033)	(0.029)	(0.026)	(0.030)	(0.025)	(0.021)	(0.021)	(0.018)	(0.016)	(0.017)	(0.021)	(0.020)
RTI	–0.014	–0.002	0.002	0.023	0.011	0.019	0.030	–0.014	–0.031	–0.049	–0.052	–0.053	–0.065	–0.068	–0.086	–0.061	–0.031	-0.020	0.000
	(0.036)	(0.020)	(0.023)	(0.019)	(0.018)	(0.018)	(0.018)	(0.017)	(0.016)	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)	(0.025)
Intercept	0.260	0.303	0.277	0.212	0.213	0.252	0.242	0.287	0.331	0.355	0.253	0.319	0.284	0.327	0.383	0.433	0.455	0.483	0.461
	(0.127)	(0.070)	(0.076)	(0.069)	(0.058)	(0.053)	(0.053)	(0.052)	(0.062)	(0.046)	(0.045)	(0.038)	(0.034)	(0.034)	(0.030)	(0.028)	(0.030)	(0.032)	(0.052)

(Continues...)

Table B6 (continued)

1993–2004	q5	q10	q15	q20	q25	q30	q35	q40	q45	q50	q55	q60	q65	q70	q75	q80	q85	q90	q95
Change	0.184	0.062	0.123	0.052	–0.011	–0.010	0.021	0.007	–0.049	–0.034	–0.007	–0.021	0.109	0.169	0.224	0.253	0.303	0.337	0.465
	(0.032)	(0.029)	(0.019)	(0.033)	(0.021)	(0.018)	(0.022)	(0.014)	(0.030)	(0.035)	(0.022)	(0.025)	(0.024)	(0.020)	(0.021)	(0.022)	(0.014)	(0.021)	(0.019)
Reweighting																			
Composition	–0.013	–0.002	0.002	0.002	0.005	0.010	0.018	0.024	0.030	0.033	0.033	0.034	0.035	0.035	0.039	0.036	0.036	0.036	0.025
	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)
Specification error	0.005	0.001	0.000	0.002	0.000	0.001	–0.001	–0.003	–0.003	0.025	–0.004	–0.007	0.025	0.013	–0.002	0.009	–0.002	–0.012	0.009
	(0.019)	(0.005)	(0.017)	(0.004)	(0.008)	(0.013)	(0.011)	(0.019)	(0.017)	(0.017)	(0.009)	(0.016)	(0.009)	(0.022)	(0.019)	(0.012)	(0.014)	(0.010)	(0.007)
Earnings structure	0.196	0.066	0.125	0.052	–0.010	–0.016	0.009	–0.008	–0.069	–0.087	–0.031	–0.042	0.057	0.127	0.195	0.215	0.275	0.319	0.437
	(0.031)	(0.026)	(0.016)	(0.031)	(0.020)	(0.019)	(0.018)	(0.022)	(0.018)	(0.028)	(0.021)	(0.022)	(0.020)	(0.019)	(0.020)	(0.011)	(0.015)	(0.020)	(0.019)
Reweighting error	–0.005	–0.003	–0.004	–0.004	–0.005	–0.005	–0.005	–0.005	–0.006	–0.005	–0.006	–0.006	–0.007	–0.007	–0.007	–0.007	–0.006	–0.006	–0.005
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Detailed earnings structure																			
Age	–0.015	0.010	0.049	0.039	0.050	0.033	0.031	0.029	0.017	0.013	0.002	0.014	0.015	0.047	0.055	0.061	0.038	0.045	0.023
	(0.025)	(0.015)	(0.014)	(0.013)	(0.013)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.011)	(0.014)	(0.013)	(0.015)	(0.014)	(0.012)	(0.013)	(0.016)
Sex	0.040	0.007	0.021	0.016	0.030	0.011	0.006	0.009	–0.006	–0.012	–0.011	–0.021	–0.030	–0.020	–0.007	–0.003	0.005	–0.007	–0.018
	(0.025)	(0.014)	(0.012)	(0.009)	(0.008)	(0.008)	(0.006)	(0.007)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.009)
Education	–0.014	–0.046	–0.087	–0.053	–0.088	–0.040	–0.055	–0.082	–0.032	–0.017	0.009	0.114	0.204	0.176	0.103	0.066	0.034	0.019	0.002
	(0.067)	(0.042)	(0.036)	(0.031)	(0.029)	(0.027)	(0.030)	(0.031)	(0.034)	(0.034)	(0.030)	(0.041)	(0.038)	(0.033)	(0.034)	(0.027)	(0.019)	(0.017)	(0.020)
Religion	–0.012	–0.014	–0.013	–0.005	–0.007	–0.009	0.003	0.004	0.006	0.013	0.006	0.000	–0.007	–0.001	–0.001	–0.002	0.001	0.000	–0.004
	(0.014)	(0.009)	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)	(0.008)
Social group	0.039	0.106	0.120	0.119	0.107	0.113	0.126	0.132	0.140	0.099	0.019	–0.028	–0.087	–0.099	–0.052	–0.034	–0.026	0.003	0.052
	(0.080)	(0.045)	(0.042)	(0.034)	(0.036)	(0.033)	(0.031)	(0.031)	(0.030)	(0.032)	(0.032)	(0.034)	(0.036)	(0.034)	(0.033)	(0.031)	(0.028)	(0.030)	(0.028)
RTI	–0.020	–0.043	–0.009	–0.007	0.001	–0.001	0.031	0.052	0.021	0.038	0.016	–0.058	–0.122	–0.144	–0.140	–0.152	–0.136	–0.149	–0.133
	(0.039)	(0.024)	(0.022)	(0.017)	(0.015)	(0.015)	(0.016)	(0.016)	(0.018)	(0.017)	(0.020)	(0.023)	(0.024)	(0.023)	(0.023)	(0.024)	(0.023)	(0.025)	(0.031)
Intercept	0.178	0.046	0.043	–0.058	–0.104	–0.123	–0.134	–0.152	–0.216	–0.221	–0.071	–0.064	0.085	0.169	0.237	0.280	0.359	0.408	0.515
	(0.128)	(0.083)	(0.065)	(0.059)	(0.055)	(0.051)	(0.052)	(0.052)	(0.053)	(0.058)	(0.048)	(0.058)	(0.064)	(0.059)	(0.052)	(0.048)	(0.043)	(0.054)	(0.057)

(Continues...)

Table B6 (continued)

2004–11	q5	q10	q15	q20	q25	q30	q35	q40	q45	q50	q55	q60	q65	q70	q75	q80	q85	q90	q95
Change	0.386	0.417	0.348	0.282	0.304	0.318	0.277	0.262	0.297	0.266	0.247	0.266	0.141	0.192	0.178	0.209	0.272	0.258	0.185
	(0.039)	(0.027)	(0.015)	(0.038)	(0.024)	(0.021)	(0.022)	(0.017)	(0.019)	(0.023)	(0.035)	(0.030)	(0.034)	(0.039)	(0.047)	(0.023)	(0.023)	(0.025)	(0.018)
Reweighting																			
Composition	0.054	0.057	0.053	0.058	0.061	0.069	0.076	0.080	0.102	0.114	0.127	0.161	0.188	0.184	0.166	0.150	0.131	0.134	0.129
	(0.010)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.011)	(0.010)	(0.013)	(0.018)	(0.019)	(0.017)	(0.017)	(0.013)	(0.014)	(0.015)
Specification error	0.047	0.043	0.020	0.056	0.058	0.018	0.033	–0.005	–0.007	–0.015	–0.038	0.055	–0.038	–0.023	–0.059	–0.011	–0.014	0.024	–0.073
	(0.026)	(0.017)	(0.006)	(0.023)	(0.019)	(0.013)	(0.007)	(0.011)	(0.012)	(0.028)	(0.018)	(0.018)	(0.026)	(0.019)	(0.014)	(0.011)	(0.016)	(0.016)	(0.027)
Earnings structure	0.284	0.316	0.275	0.167	0.185	0.230	0.167	0.186	0.201	0.166	0.156	0.047	–0.012	0.028	0.069	0.068	0.152	0.098	0.127
	(0.033)	(0.017)	(0.014)	(0.019)	(0.016)	(0.020)	(0.017)	(0.016)	(0.019)	(0.024)	(0.026)	(0.022)	(0.028)	(0.034)	(0.038)	(0.019)	(0.020)	(0.023)	(0.029)
Reweighting error	0.001	0.001	0.000	0.000	0.000	0.001	0.000	0.001	0.001	0.001	0.002	0.003	0.003	0.003	0.002	0.002	0.003	0.002	0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Detailed earnings structure																			
Age	0.067	0.046	0.040	0.013	0.013	0.013	0.020	0.023	0.014	0.015	–0.007	–0.012	–0.011	–0.006	0.002	0.017	0.012	0.000	0.010
	(0.020)	(0.015)	(0.012)	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)	(0.011)	(0.012)	(0.013)	(0.015)	(0.015)	(0.015)	(0.016)	(0.014)	(0.014)	(0.014)	(0.016)
Sex	–0.031	0.018	0.033	0.006	0.007	0.005	0.002	0.006	0.001	0.001	0.002	0.008	–0.001	–0.011	–0.009	–0.010	0.002	0.012	0.024
	(0.022)	(0.013)	(0.009)	(0.009)	(0.008)	(0.007)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.009)
Education	0.172	0.037	–0.023	0.015	–0.013	–0.084	–0.048	–0.077	–0.119	–0.088	–0.098	–0.159	–0.016	0.141	0.088	0.076	0.076	0.009	0.005
	(0.073)	(0.046)	(0.036)	(0.037)	(0.036)	(0.039)	(0.039)	(0.043)	(0.040)	(0.044)	(0.050)	(0.043)	(0.053)	(0.039)	(0.033)	(0.025)	(0.025)	(0.022)	(0.018)
Religion	0.032	0.018	0.004	0.000	0.002	0.004	0.000	–0.001	–0.005	0.003	0.014	0.017	0.013	0.006	0.012	0.000	0.000	–0.005	–0.007
	(0.012)	(0.009)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Social group	0.049	0.044	0.030	–0.004	0.011	0.008	0.013	–0.007	–0.006	0.043	0.034	0.071	0.113	0.072	0.034	0.046	0.026	0.012	–0.013
	(0.061)	(0.043)	(0.032)	(0.033)	(0.030)	(0.029)	(0.027)	(0.031)	(0.029)	(0.036)	(0.037)	(0.037)	(0.037)	(0.040)	(0.038)	(0.034)	(0.032)	(0.032)	(0.027)
RTI	0.007	0.021	0.055	0.026	0.010	0.021	–0.001	0.035	0.058	0.058	0.079	0.117	0.072	–0.005	0.000	–0.018	0.003	0.016	–0.002
	(0.033)	(0.020)	(0.018)	(0.020)	(0.020)	(0.018)	(0.020)	(0.021)	(0.016)	(0.018)	(0.024)	(0.020)	(0.027)	(0.023)	(0.021)	(0.020)	(0.020)	(0.020)	(0.022)
Intercept	–0.012	0.131	0.136	0.111	0.155	0.263	0.181	0.207	0.258	0.135	0.133	0.005	–0.183	–0.167	–0.057	–0.042	0.033	0.054	0.110
	(0.118)	(0.075)	(0.056)	(0.057)	(0.054)	(0.062)	(0.051)	(0.057)	(0.056)	(0.058)	(0.063)	(0.060)	(0.057)	(0.077)	(0.078)	(0.057)	(0.056)	(0.053)	(0.053)

(Continues...)

Table B6 (continued)

2011–17	q5	q10	q15	q20	q25	q30	q35	q40	q45	q50	q55	q60	q65	q70	q75	q80	q85	q90	q95
Change	0.106	0.108	0.075	0.216	0.178	0.106	0.153	0.112	0.084	0.075	–0.015	0.008	–0.020	–0.047	–0.137	–0.151	–0.141	–0.061	–0.085
	(0.050)	(0.020)	(0.030)	(0.017)	(0.025)	(0.018)	(0.019)	(0.021)	(0.028)	(0.014)	(0.032)	(0.021)	(0.043)	(0.037)	(0.051)	(0.028)	(0.031)	(0.019)	(0.016)
Reweighting																			
Composition	–0.006	–0.002	0.002	0.012	0.016	0.016	0.020	0.022	0.023	0.030	0.043	0.048	0.060	0.072	0.069	0.063	0.060	0.049	0.043
	(0.010)	(0.007)	(0.006)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.011)	(0.012)	(0.014)	(0.016)	(0.016)	(0.014)	(0.014)	(0.012)	(0.010)
Specification error	0.043	0.009	0.007	0.003	0.018	–0.027	0.015	0.000	0.001	–0.077	–0.021	–0.005	0.008	0.020	0.011	–0.032	–0.084	–0.020	–0.006
	(0.018)	(0.009)	(0.003)	(0.012)	(0.011)	(0.025)	(0.010)	(0.018)	(0.020)	(0.031)	(0.016)	(0.014)	(0.014)	(0.020)	(0.021)	(0.014)	(0.029)	(0.014)	(0.022)
Earnings structure	0.068	0.101	0.065	0.200	0.142	0.116	0.118	0.089	0.060	0.121	–0.037	–0.035	–0.090	–0.140	–0.218	–0.184	–0.120	–0.092	–0.123
	(0.048)	(0.018)	(0.032)	(0.011)	(0.025)	(0.015)	(0.013)	(0.022)	(0.029)	(0.027)	(0.024)	(0.014)	(0.031)	(0.025)	(0.028)	(0.025)	(0.036)	(0.018)	(0.027)
Reweighting error	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.002	0.002	0.002	0.002
	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Detailed earnings structure																			
Age	–0.030	–0.013	–0.015	–0.003	–0.004	–0.008	–0.013	–0.013	–0.007	–0.023	–0.029	–0.041	–0.054	–0.067	–0.015	0.008	0.021	0.047	0.042
	(0.019)	(0.013)	(0.014)	(0.010)	(0.010)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)	(0.012)	(0.015)	(0.015)	(0.014)	(0.015)	(0.014)	(0.017)
Sex	–0.025	–0.031	–0.037	0.002	–0.011	0.001	0.006	0.004	0.015	–0.003	0.006	0.001	0.007	0.003	0.000	–0.006	0.001	0.001	0.002
	(0.028)	(0.016)	(0.013)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)	(0.007)	(0.005)	(0.006)	(0.006)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Education	–0.103	–0.003	0.044	0.011	0.036	–0.024	–0.077	–0.070	–0.074	–0.116	–0.169	–0.165	–0.116	–0.125	0.069	0.148	0.096	0.136	0.075
	(0.079)	(0.053)	(0.041)	(0.038)	(0.033)	(0.029)	(0.030)	(0.030)	(0.032)	(0.032)	(0.034)	(0.037)	(0.043)	(0.040)	(0.048)	(0.033)	(0.037)	(0.021)	(0.019)
Religion	–0.016	–0.011	–0.005	–0.005	–0.004	–0.003	–0.004	–0.002	–0.003	–0.003	–0.010	–0.005	–0.011	–0.007	–0.005	0.004	0.007	0.002	0.012
	(0.011)	(0.007)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.007)
Social group	0.053	0.054	0.043	0.069	0.041	0.041	0.055	0.058	0.048	0.040	0.082	0.091	0.032	0.026	0.014	–0.023	–0.020	–0.063	–0.038
	(0.056)	(0.042)	(0.028)	(0.028)	(0.029)	(0.027)	(0.027)	(0.027)	(0.025)	(0.023)	(0.026)	(0.026)	(0.034)	(0.035)	(0.031)	(0.030)	(0.033)	(0.031)	(0.033)
RTI	0.005	0.029	–0.019	0.013	0.033	0.024	0.042	0.045	0.033	0.046	0.077	0.063	0.071	0.099	0.022	–0.005	0.005	–0.011	0.010
	(0.036)	(0.023)	(0.017)	(0.017)	(0.018)	(0.015)	(0.016)	(0.017)	(0.015)	(0.016)	(0.020)	(0.017)	(0.023)	(0.023)	(0.025)	(0.021)	(0.017)	(0.013)	(0.015)
Intercept	0.184	0.077	0.054	0.113	0.052	0.085	0.107	0.065	0.047	0.181	0.005	0.020	–0.017	–0.069	–0.303	–0.310	–0.230	–0.206	–0.228
	(0.115)	(0.071)	(0.056)	(0.048)	(0.048)	(0.042)	(0.041)	(0.050)	(0.068)	(0.050)	(0.053)	(0.050)	(0.064)	(0.068)	(0.069)	(0.066)	(0.067)	(0.047)	(0.044)

Note: bootstrapped standard errors in parentheses (100 replications). The sample includes urban, non-agricultural, paid workers. Country-specific RTI at two-digit level is used to control for RTI of an occupation. Period-specific quantiles are utilized.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.

Table B7: Decomposition of the change in earnings (log): RIF regression using O*NET RTI at two-digit level (paid, non-agricultural, urban)

	1983–2017		1983–93		1993–2004		2004–11		2011–17	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Change	–0.006	0.000	0.005	0.000	0.003	0.001	–0.006	0.001	–0.009	0.001
Reweighting										
Composition	–0.001	0.000	0.000	0.000	0.001	0.000	0.000	0.000	0.000	0.000
Earnings structure	–0.006	0.001	0.005	0.000	0.002	0.001	–0.005	0.001	–0.009	0.000
RIF										
Composition	0.004	0.000	0.000	0.000	0.002	0.000	0.001	0.000	0.001	0.000
Specification error	–0.004	0.000	0.000	0.000	0.000	0.000	–0.001	0.000	–0.001	0.000
Earnings structure	–0.005	0.001	0.005	0.000	0.002	0.001	–0.005	0.001	–0.009	0.000
Reweighting error	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Detailed earnings structure										
Age	0.000	0.000	0.000	0.000	0.000	0.000	–0.002	0.000	0.001	0.000
Sex	–0.001	0.000	0.000	0.000	–0.001	0.000	0.000	0.000	0.000	0.000
Education	0.009	0.002	0.002	0.001	0.004	0.001	0.000	0.001	0.001	0.002
Religion	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Social group	–0.003	0.002	0.000	0.002	–0.004	0.002	0.001	0.001	–0.003	0.001
RTI	–0.004	0.001	–0.001	0.001	0.000	0.001	–0.004	0.001	0.000	0.001
Industry	–0.008	0.001	–0.004	0.001	–0.001	0.001	–0.002	0.001	0.000	0.001
Intercept	0.001	0.003	0.008	0.002	0.003	0.002	0.002	0.002	–0.007	0.002

Note: the sample includes urban, non-agricultural, paid workers. O*NET RTI at two-digit level is used to control for RTI of an occupation.

Source: authors' calculations based on NSS 1983, 1993, 2004, and 2011, and PLFS 2017.