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The changing nature of work and inequality in Brazil (2003–19)

A descriptive analysis

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Abstract: In this paper we use different sources of data on job task content to investigate the importance of occupations and the intensity of routine tasks embodied in them in explaining changes in employment and earnings in Brazil, in particular their relation with earnings and polarization, and inequality. We show some evidence of polarization in earnings but not with respect to employment, although the patterns resemble more that of pro-poor or pro-rich growth. Changes in the earnings structure explain most of the reduction in inequality in the period between 2003 and 2012, while changes in composition dominate the rise in inequality in the period between 2012 and 2019. Both movements are dominated by changes in educational levels and their returns. The impact of changes in routine task content on inequality varies between both periods but is in general small.

Key words: Brazil, inequality, polarization, task content, occupations

JEL classification: J21, J24, D63, N36

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1 Introduction

In recent years, researchers in labour economics have advocated for the empirical and theoretical fruitfulness of a distinction between 'skills' (worker capabilities, whether innate or acquired by training) and 'tasks' (units of work activity that directly participate in production) (see, for instance, Acemoglu and Autor 2011; Fortin et al. 2011). It has been argued that models that overemphasize the role of skills in the determination of labour earnings and composition end up missing important features of recent labour market trends, at least in developed countries. Therefore, 'task approaches' (Autor 2013) are now extensively used to describe in a more nuanced way how the most recent technological revolutions, openness to trade, and offshoring altered the structure of labour demand and, thereby, the employment structure and labour earnings distribution. In this framework, occupations assume a prominent role, since the task content of work is typically determined at the occupational level.

Despite the agreement on the contribution that 'task approaches' have made to a better understanding of the job market trends in advanced economies (Acemoglu and Autor 2011; Autor and Dorn 2013; Goos et al. 2014; Sebastian 2018), there are still few applications to developing and under-developed economies. This paper contributes to our understanding of the joint roles of 'skills' and 'tasks' in shaping the evolution of employment and earnings distribution, using Brazil as a case study.

Brazil is a particularly interesting country for a couple of reasons. It has historically been characterized by high levels of inequality, even by Latin American standards. Starting in the mid-1990s, Brazil went through two decades of continuous reductions in inequality, with respect to both labour and non-labour income. This decline has been extensively studied,[1] and it provides an important background to assess the importance of occupations and their task content in developing countries, in contrast to other factors that also affect labour markets. This long period of declining inequality has recently come to an end, with inequality in Brazil rising since 2015. Our analyses, which spans the years 2003–19, covers both the inequality-decreasing and inequality-increasing time intervals.

Our objective in this paper is twofold. First, we document shifts in the employment structure in Brazil, highlighting the role of occupations and their task content, and how they have evolved over time. In particular, we use measures of job task content that rely on country-specific information and contrast this to results obtained using measures based on US data, therefore departing from the assumption of uniformity with respect to job content (Lewandowski et al. 2019). Second, we evaluate how occupations and their task content are associated with changes in polarization and inequality in Brazil. We evaluate the hypothesis of polarization in employment and earnings in Brazil, with respect to both initial earnings and routine task content. We also assess the importance of occupations and their routine task content in explaining inequality and the changes observed in the period. In particular, we test whether routine task content has any relation to changes in earnings inequality after we account for changes in skills and other factors.

Our results show a considerable association between occupations' average earnings and their task content, especially if we consider country-specific measures of routine task content. Jobs that are more intensive in routine tasks in Brazil are the ones with the lowest earnings. Between-jobs inequality accounts for nearly half of overall inequality, although its relevance has declined over time. Earnings inequality between occupations is similar to concentration indices that order individuals by routine task content of their occupations instead of earnings, highlighting the importance of job task content in Brazil.

Despite the fact that the Brazilian economy has not changed dramatically in the last two decades, we find a declining intensity of routine tasks across the whole economy, a precondition for polarization as

[1] See, for instance, Firpo and Portella (2019) and Neri (2021).

found in developed countries. We find some evidence of earnings polarization, but not with respect to employment. However, the patterns resemble much more those of pro-poor or pro-rich growth rather than polarization itself, as we find no evidence of hollowing out in the middle of the distribution.

When we look at changes in overall inequality, we find that the reduction in the Gini coefficient in the first period is mostly explained by changes in the structure of returns, while the rise in the second period is mostly determined by changes in the composition of workers. The supply of skilled labour and changes in its return are the main factors driving these results. Our results thus reinforce previous conclusions with respect to the dual role of education in affecting inequality, in what has been called the 'paradox of progress'. With respect to the routine task intensity (RTI) of occupations, we observe a composition effect in the first period, but an inequality-enhancing effect in the second. Returns to RTI contribute to reducing inequality in the whole period, but its effect is small, not always significant, and measures based on country-specific or O*NET information vary. Finally, when we include RTI into our inequality decomposition, we see that the part explained by educational levels—both composition and structure—reduce in magnitude, although both remain significant.

The remainder of the paper is structured as follows. Section 2 presents our survey data and the aggregate measures of job task content. Section 3 discusses the methodology employed in our analysis. We conduct a descriptive analysis of the Brazilian economy in Section 4, examining the main factors associated with labour market outcomes, as well as changes in the occupational structure. The results of our main analyses are presented in Section 5, including a discussion of polarization, inequality, and the role of occupations in accounting for them. Section 6 concludes.

2 Data

2.1 Demographics, employment, and earnings

Our main sources of data are the Brazilian National Household Sample Survey ('*Pesquisa Nacional por Amostragem de Domicílios*', PNAD) and the Continuous Brazilian National Household Sample Survey ('*Pesquisa Nacional por Amostra de Domicílios Contínua*', PNADC), both conducted by the Brazilian Institute of Geography and Statistics. In 2015 the PNAD was replaced by the PNADC, which is a rotating-panel version of the former.[2] Thus, the PNAD covers the years 2003–09 and 2011–15, while the PNADC covers the years 2016–19.[3] Both surveys are nationally representative and investigate several characteristics of the population, such as education, labour (with occupational information for the employed), income, and fertility. On average, sample sizes are 258,382 in the PNAD and 311,575 in the PNADC.

We now describe the variables we use throughout our analysis. We use effective earnings from the main work activity, converted to 2012 real weekly values.[4] The working status variable is defined using the employment event in the survey reference week. Workers are divided between formal employees, which are those with legal labour contracts (a signed 'labour' booklet or *com carteira*); informal employees, which are those without legal labour contracts; and self-employed workers. Self-employed workers are further divided into those that contribute to social security (INSS) and those that do not. When specifically stated as such, self-employed workers that contributed to INSS are put together with

[2] We use the annual version of the PNADC comprising only households interviewed for the first time.

[3] There was no survey in 2010 because it was a Census year.

[4] We adjust all values to constant October 2012 prices using the Brazilian price deflator for personal consumption (*Índice Nacional de Preços ao Consumidor—Restrito*, INPC), as recommended by Corseuil and Foguel (2002).

formal employees in a wider formality definition. We restrict our analysis to individuals between 15 and 64 years old, dividing them into three categories (15–24, 25–44, 45–64). Our racial variable has five categories: White, Black, Brown (*Pardo*), Indigenous, and Asian descendent. We also have information on gender and geography (27 Brazilian states and rural residency). We use the second version of the Brazilian Classification of Economic Activities (CNAE 2.0) to classify workers according to their sector of activity.

Our analysis relies heavily on the use of occupations. We use ISCO-88 (the International Standard Classification of Occupations) at the three-digit level to classify workers' occupations. However, both the PNAD and PNADC use Brazilian classification systems that slightly differ between themselves and also with respect to ISCO-88. The PNAD uses the Brazilian Classification of Occupations (*Classificação Brasileira de Ocupações - Domiciliar*, CBO-D), while the PNADC uses the National Classification of Occupations for Household Surveys (*Classificação Nacional de Ocupações para Pesquisas Domiciliares*, COD). The matching between both classifications is described in detail in Appendix B and relies on the 2010 Demographic Census, which classified workers according to both systems. Appendix B also describes our crosswalk between CBO-D and ISCO-88.

2.2 Task content measures

Our analysis relies not only on the harmonized classification of occupations over time, but also on their task content, especially their RTI. To create this measure, we join our data from the PNAD and PNADC with O*NET data based on the results in Lewandowski et al. (2019, 2020). The assumption is that, given the differences in technology adoption, labour productivity, and skill supply, specific occupations utilize different skill sets and assign different tasks from low-income to high-income countries. In particular, richer countries tend to specialize in non-routine tasks and poorer countries in routine tasks.

According to Autor et al. (2003), tasks can be classified by considering two dimensions: routine vs non-routine and manual vs cognitive. Routine tasks are those characterized by a set of repetitive actions that can be accomplished by following explicit rules. Non-routine activities are those that change in time. Manual tasks demand physical activities, while cognitive tasks are those that require information processing, programming, creativity, and problem solving. We construct country-specific task measures for Brazil using RTI measures based on the previous literature (Autor and Dorn 2013; Goos et al. 2014), as well as a measure based on information from O*NET (2003). Following Lewandowski et al. (2019, 2020), the RTI is a composite measure based on four constructed task measures:

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

where $r_{cognitive}$ and r_{manual} are the routine cognitive tasks and the routine manual tasks, respectively, and $nr_{analytical}$ and $nr_{personal}$ are the non-routine cognitive analytical tasks and the non-routine cognitive personal tasks, respectively. The routine/non-routine and the manual/cognitive tasks are characterized as before. The analytical one is based on solving problems, programming, and reading journals, while the personal one is based on supervising others and presentations. This definition omits non-routine manual tasks from the analysis used in the original approach by Autor and Dorn (2013) because, according to Lewandowski et al. (2019), routine and non-routine manual tasks are highly correlated. We match the O*NET and survey task content measures to the PNAD and PNADC data at the occupational level, using ISCO-88 occupational units at the three-digit level. For more details on the coding of occupations, see Appendix B.

3 Methodology

We conduct three main exercises in our empirical analysis.[5] The first analysis aims at evaluating job polarization at the occupational level in Brazil, both in terms of employment and earnings. To do so, we aggregate individuals at the three-digit level of ISCO-88 and regress change in log employment shares and log mean weekly earnings on initial log mean weekly earnings and its square (Goos and Manning 2007; Sebastian 2018):

$$\Delta \log (y_{j,t}) = \varphi_0 + \varphi_1 \log (x_{j,t-1}) + \varphi_2 \log (x_{j,t-1})^2 + \varepsilon_{j,t} \tag{2}$$

where $\Delta \log (y_{j,t})$ represents either changes in log employment share or changes in log mean earnings in occupation j between periods $t-1$ and t. The independent variable, $\log (x_{j,t-1})$, and its square refer to log of mean earnings in occupation j in the initial period, $t-1$. Occupations are weighted by their initial share in total employment.

In a next step we run the same regressions with the same dependent variables, but replace the explanatory variables—log of mean earnings and its square—with the initial level of RTI and its square (Sebastian 2018):

$$\Delta \log (y_{j,t}) = \vartheta_0 + \vartheta_1 (RTI_j) + \vartheta_2 (RTI_j)^2 + \varepsilon_{j,t} \tag{3}$$

In our second analysis we evaluate the importance of occupations in explaining trends in overall inequality. To do so, we perform Shapley decompositions (Shorrocks 2013) of the Gini index using occupations to group individuals. That is, we measure how much of the Gini index is determined within and between occupations, following the approach proposed by Gradín and Schotte (2020):

$$G = G_B + G_W \tag{4}$$

where G is the overall Gini index, G_B is the Gini index between occupations, and G_W is the Gini index within occupations. Those two are defined by:

$$\begin{aligned} G_B &= \frac{1}{2}\left[G(y_b) + G - G(y_w)\right] \\ G_W &= \frac{1}{2}\left[G(y_w) + G - G(y_b)\right] \end{aligned} \tag{5}$$

The vector y_b is a vector in which earnings of all workers are replaced by the average earnings of their respective occupation j, while y_w is the vector of earnings rescaled so that all occupations have the same average earnings.[6] Hence, $G(y_w)$ and $G(y_b)$ are simply the Gini index computed based on these alternative vectors of earnings, instead of $G = G(y)$, the actual Gini index computed using the actual vector of earnings, y.

This decomposition is then complemented by also decomposing the change in between-occupations inequality, ΔG_B, into a factor associated with changes in the share of workers employed in each occupation and changes in average earnings of each occupation. Let ΔG_{bm} denote the change in between-occupation inequality across two time periods in the counterfactual scenario when employment shares are kept constant as in the initial period. Similarly, let ΔG_{be} denote the counterfactual change when average earnings in each occupation are held constant as in the first period.

Based on these two counterfactual scenarios, we can again apply the Shapley methodology and decompose changes in between-occupations inequality into a component driven by changes in employment

[5] Unless stated otherwise, we closely follow the approach of Gradín and Schotte (2020), and refer readers to their methodological appendix for further details.

[6] See the methodological appendix of Gradín and Schotte (2020) for further details.

shares and another driven by mean earnings, ΔG_{BE} and ΔG_{BM}, respectively:

$$\Delta G_B = \Delta G_{BE} + \Delta G_{BM} \tag{6}$$

$$\Delta G_{BE} = \frac{1}{2}\left[\Delta G_{be} + \Delta G_B - \Delta G_{bm}\right] \tag{7}$$

$$\Delta G_{BM} = \frac{1}{2}\left[\Delta G_{bm} + \Delta G_B - \Delta G_{be}\right] \tag{8}$$

Occupations can have an impact on inequality through many channels. For instance, occupations demand different skill sets and the returns to them may vary. Similarly, the task content embodied in each occupation is diverse and can have different returns. To capture this last possibility, we compute the RTI concentration index for the distribution of average earnings by occupation. While in the conventional Gini between occupations, $G(y_b)$, occupations are sorted by their average earnings, in the RTI concentration index they are sorted by their (inverted) routine task intensity.

As will be shown later, there is a negative correlation between the intensity of routine tasks in occupations and their average earnings. If this correlation was perfect, the Gini index between occupations and the RTI concentration index would be identical. We use the ratio between these two indices as a measure of association between RTI and average earnings. This provides evidence on the extent to which between-occupations inequality is linked with RTI or with other factors associated with occupations.

Finally, we apply the recentred influence functions (RIF) methodology (Firpo et al. 2009, 2011, 2018; Fortin et al. 2011) to decompose the changes in functionals of the earnings distributions across time. This approach can be used to attribute changes in inequality to workers' characteristics (composition effects) and the returns to these characteristics (structure effects).

Formally, distributional parameters such as the Gini index or interquantile ratios can be written as functionals $v(F_y)$, where F_y is the cumulative distribution function of the earnings distribution y. The influence function of a statistic v, $IF(y;v)$, quantifies the impact of a marginal change in the population mass at some point y on the statistic v, and has an expected value of zero. The RIF, $RIF(y;v)$, is obtained by adding v, such that $RIF(y;v) = IF(y;v)$ and thus $E_y[RIF(y;v)] = v$.

To assess the impact of different workers' characteristics, X, on an inequality measure, $v(F_y)$, let $F_{y_s|t}$ be the earnings distribution when workers in period t are remunerated under the earnings structure prevailing at period s. Therefore, $F_{y_0|t=0}$ and $F_{y_1|t=1}$ are observed, as well as their functionals $v(F_{y_0|t=0})$ and $v(F_{y_1|t=1})$.

There are two ways in which we can decompose changes in $v(F_y)$ across time. In the first, we perform the traditional Oaxaca–Blinder (OB) decomposition (Blinder 1973; Oaxaca 1973) by assuming the following linear structure for the conditional expectation of the RIF:

$$E[\mathrm{RIF}(y_{it};v)\,|X_i, Time = t] = \gamma_t X_{it}, \text{ for } t = 0,1 \tag{9}$$

Therefore, we can write changes in time in the expected value of the functional v as:

$$\begin{aligned} v(F_{y_1|t=1}) - v(F_{y_0|t=0}) &= E[\mathrm{RIF}(y_{i1};v)\,|t=1] - E[\mathrm{RIF}(y_{i0};v)\,|t=0] \\ &= \gamma_1 X_{i1} - \gamma_0 X_{i0} \\ &= (\gamma_1 - \gamma_0)X_{i1} + \gamma_0(X_{i1} - X_{i0}) \end{aligned} \tag{10}$$

where the first term corresponds to changes in the functional v accounted for by changes in the structure, and the second term changes are accounted for by changes in the composition of workers' characteristics.

The second method consists of two steps. In the first step we estimate the counterfactual distribution, $F_{y_0|t=1})$, which gives the distribution of earnings under the structure of $t = 0$ for workers at time $t = 1$. In this case, the aggregate decomposition of the observed difference in functional v is:

$$\begin{aligned}\Delta_o^v &= v\left(F_{y_1|t=1}\right) - v\left(F_{y_0|t=0}\right) \\ &= \left[v\left(F_{y_1|t=1}\right) - v\left(F_{y_0|t=1}\right)\right] + \left[v\left(F_{y_0|t=1}\right) - v\left(F_{y_0|t=0}\right)\right] \\ &= \Delta_S^v \quad + \quad \Delta_X^v \end{aligned} \tag{11}$$

This counterfactual is estimated using reweighting and is consistent under the ignorability and common overlapping assumptions (Firpo et al. 2018).

For the detailed decomposition, we again assume a linear relationship for the RIF, now including the counterfactual distributions of (y_c, X_c) obtained by reweighting:

$$E[\text{RIF}(y_{i0}; v) \,|Time = 1] = \gamma_c X_{ic} \tag{12}$$

Then, the decomposition consists of four components:

$$\begin{aligned}\Delta_o^v &= \Delta_S^v \quad + \quad \Delta_X^v \\ &= (\gamma_1 - \gamma_c) X_{i1} + \gamma_c (X_{i1} - X_{ic}) + \gamma_0 (X_{ic} - X_{i0}) + (\gamma_c - \gamma_0) X_{ic} \\ &= \Delta_{S,p}^v \quad + \quad \Delta_{S,e}^v \quad + \quad \Delta_{X,p}^v \quad + \quad \Delta_{X,e}^v \end{aligned} \tag{13}$$

These four terms are: the pure structure effect, $\Delta_{S,p}^v$; the reweighting error, $\Delta_{S,e}^v$; the pure composition effect, $\Delta_{X,p}^v$; and the specification error, $\Delta_{X,e}^v$.

The two error terms provide an evaluation of the quality of the decomposition. The reweighting error, $\gamma_c (X_{i1} - X_{ic})$, arises because the reweighting procedure is unable to perfectly replicate the distribution of workers' characteristics observed in $t = 1$, and should disappear asymptotically.

The specification error, $(\gamma_c - \gamma_0) X_{ic}$, arises because of departures of the linearity assumption imposed by Equation 12, and its size reflects how much the estimated RIF coefficients vary after we reweight the distribution of workers' characteristics in $t = 0$ to equal that observed in $t = 1$. Therefore, the specification error reflects a form of composition effect, as it measures the indirect effects of changes in workers' characteristics on the estimated coefficients. In this paper we apply both forms of decomposition, highlighting their differences and the role played by specification errors.

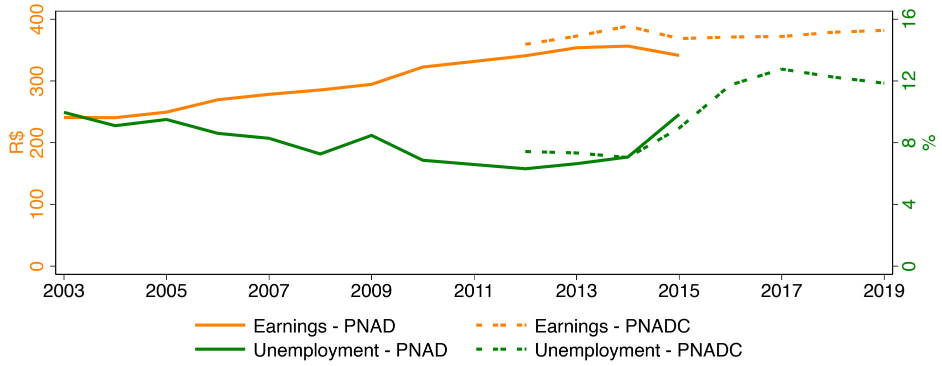
4 The Brazilian economy between 2003 and 2019

In the first decade of the twenty-first century, and up to the mid-2010s, Brazil underwent considerable economic expansion that has resulted in increased average wages and lower unemployment rates. Figure 1 shows that average real weekly earnings increased from a little under 250 to almost 350 Brazilian *reais* between 2003 and 2015, while unemployment rates fell from around 12 to 6 per cent. However, 2015 marks the beginning of an ongoing recession that increased unemployment rates to more than 12 per cent in a few years, while real average earnings remain at the same level as in 2014.

The Brazilian boom and bust had consequences for inequality as well. Figure 2 shows the evolution of the Gini coefficient for labour earnings between 2003 and 2019. Concomitant with the economic expansion, there was a fast reduction in inequality between 2003 and 2015. However, inequality has increased marginally since then, stalling progress made at least since the inflation stabilization in 1994.[7]

[7] Based on data between 2012 and 2015, when the PNAD and PNADC overlap, we can see that inequality measured using PNADC data is higher than that with PNAD data. Both of them cover the same population and are nationally representative. To the best of our knowledge there is no study examining why these sources diverge, although they do follow a similar trend.

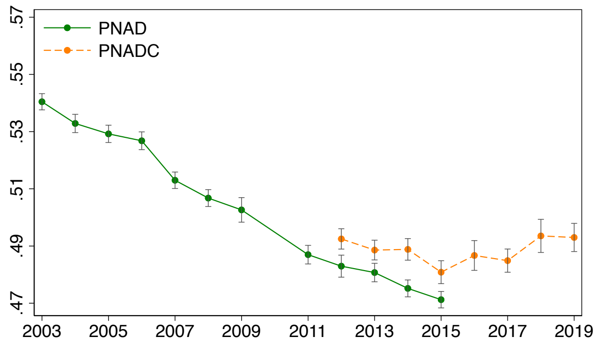
Figure 1: Average weekly earnings and unemployment rate in Brazil



Note: earnings and unemployment rates are computed based on the population between 15 and 64 years old. Earnings are deflated using the consumer index (IPCA) and 2012 as the base year.

Source: authors' compilation based on data from the PNAD (2003–09 and 2011–15) and annual PNADC (2012–19).

Figure 2: Gini coefficient in Brazil for labour earnings, 2003–19



Note: this figure plots Gini coefficients and its robust confidence intervals. Earnings are deflated to 2012 Brazilian reais.

Source: authors' compilation based on data from the PNAD (2003–09 and 2010–15) and the PNADC (2012–15).

The causes of the decrease in labour inequality up to the mid-2010s and its increase thereafter are still under debate. Firpo and Portella (2019) conduct a large survey of the literature and point to several factors that may have contributed to the fall in wage inequality up to 2015. These include changes in the supply of skilled labour, changes in the demand for labour spurred by trade liberalization and the commodities boom, as well as institutional factors associated with formality in the labour market and increases in the minimum wage.[8]

An important factor that has been neglected in the literature on inequality in Brazil is the role played by changes in occupational structure and polarization. Although some assessment of polarization can be found elsewhere (Maloney and Molina 2016), there has not been any systematic study evaluating how polarization might be associated with occupation structure and whether it can be linked to changes in inequality. In the remainder of this section we provide a more detailed picture of the evolution of the Brazilian economy in the 2000s and 2010s, before analysing the particular role of occupation and RTI in the changes in inequality observed in the period.

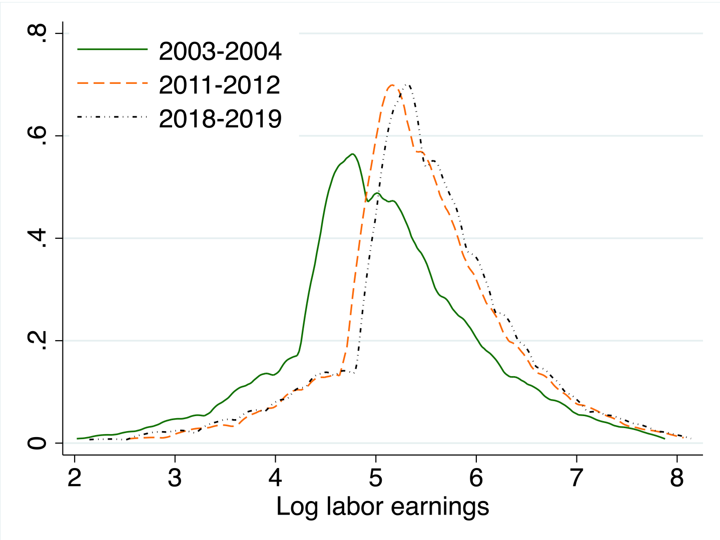
We will focus our analysis on three periods: 2003/04, 2011/12, and 2018/19. This choice not only provides intervals of similar lengths, but also captures well trends in the Brazilian economy. The first interval comprises the period of rapid economic expansion and inequality reduction, while the later period is characterized by stagnation and marks the end of two decades of inequality reduction in Brazil.

[8] For a comprehensive analysis of the reduction in income inequality in the same period, including non-labour income, see Neri (2021).

4.1 Changes in earnings distributions

Figure 3 plots the distribution of labour earnings in the three periods under analysis. There was a considerable change between the first and second periods, which led to a substantial drop in inequality. Not only was there a clear increase in average earnings, noticeable by a shift of the distribution to the right, but the probability mass in the lower tail of the distribution also reduces significantly. Between the second and third periods, however, the two distributions are alike, with only a small change of the centre of the distribution to the right, while the tail and top of the distribution remain almost the same.

Figure 3: Density of log earnings for three different time periods

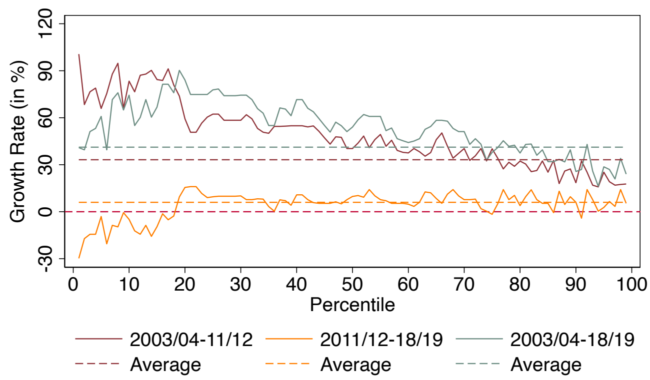


Note: the figure plots the estimated densities for the log of labour earnings. Kernel densities are estimated using the Epanechnikov function and Silverman's (1986) 1optimal' bandwidth.

Source: authors' compilation based on data from the PNAD (2003/04 and 2011/12) and PNADC (2018/19).

The patterns observed in Figure 3 are confirmed by the growth incidence curves displayed in Figure 4. We observe a clear increase in average earnings when comparing the first period with the second and third periods, while average gains are small between 2011/12 and 2018/19. However, the most important change is the end of the pro-poor growth pattern that characterized the early period, with larger increases in real income for the bottom 20 per cent of the earnings distribution. This group experienced a significant drop in earnings in the later period, while the rest of the distribution remained more or less stable.

Figure 4: Growth incidence curve by percentiles



Note: this figure plots growth incidence curves of positive real earnings by percentile during three time periods (pooled cross-sections for 2003/04, 2011/12, 2018/19). All estimates are computed using the survey individual weights. Values are deflated to October 2012.

Source: authors' compilation based on data from the PNAD and PNADC.

Figures 3 and 4 also provide some preliminary evidence on the patterns we described previously for developed countries. Based on them, we cannot conclude that the distribution of earnings is hollowing out in its middle part. This would be consistent with the configuration of a more bi-modal shape in the densities (Figure 3) or with a U-shaped form for the growth incidence curve (Figure 4). None of the figures suggest either phenomena for the period under analysis.

The consequences of these changes in the earnings distribution in terms of earnings inequality are summarized in Table 1. The interquantile ratios show that between 2003 and 2012 inequality reduced at both ends of the distribution. In the second period, however, inequality increased only with respect to the bottom of the distribution, reflecting the considerable losses this group suffered in the second period of analysis. The ratio between earnings of the 90th and 10th percentiles went from 2.04 in 2011/12 to 2.31 in 2018/19, almost reversing the reduction observed between 2003 and 2012. The ratios between the 90th and the 50th percentiles, however, remained basically the same in both periods, reflecting the stability of earnings observed in Figure 4.

Table 1: Interquantile ratios and summary inequality indices

	Interquantile ratios				Summary indices		
	2003/04	2011/12	2018/19		2003/04	2011/12	2018/19
ln(q90)–ln(q10)	2.46	2.04	2.31	Var (log earn)	0.966	0.769	0.892
ln(q90)–ln(q50)	1.36	1.16	1.18	Gini (log earn)	0.106	0.085	0.089
ln(q50)–ln(q10)	1.10	0.88	1.12	Gini (earn)	0.536	0.485	0.493

Note: this table presents summary statistics on distribution across three time periods (pooled cross-sections for 2003/04, 2011/12, and 2018/19). Prices are deflated to October 2012.

Source: authors' compilation based on data from the PNAD (2003–12) and PNADC (2018-19).

The summary indices of inequality in Table 1 show an unambiguous decrease in inequality in the first period and a slight increase in the second. Whether we measure the variance of log earnings or the Gini we observe a considerable reduction in inequality between 2003/04 and 2011/12. In the second period, however, the variance of log earnings increased substantially, while the Gini index (measured using earnings or their log) remains basically stable.

The evidence so far shows that the period between 2003/04 and 2011/12 was characterized by considerable pro-poor growth that resulted in an unambiguous fall in inequality. In the second period, growth stalled and the lower part of the earnings distribution even observed some losses. Inequality remained almost stable overall, but interquantile ratios capture a more noticeable increase in inequality in the bottom of the distribution.

4.2 Occupations and earnings

Table 2 shows how the share of formal, informal, and self-employed workers[9] changed in the period under analysis in both the agriculture and non-agriculture sectors.

[9] Formal workers are dependent employees with legal labour contracts signed by their employers in the so-called 'labour booklet' (*carteira de trabalho*), while informal workers are dependent employees without such contracts. Self-employed workers are independent workers that may or may not have legalized their activities or contributed towards the social security system.

Table 2: Distribution of workers by status in employment (%), 2003/04–2018/19

Status	Male workers			Female workers			All workers		
	2003/04	2011/12	2018/19	2003/04	2011/12	2018/19	2003/04	2011/12	2018/19
Non-agriculture									
Formal workers	42.92	51.64	48.06	46.08	55.62	53.5	44.5	53.63	50.78
Informal workers	18.96	15.11	15.1	33.59	26.79	24.3	26.28	20.95	19.7
Self-emp. workers	19.95	19.39	24.72	16.41	14.28	19.68	18.18	16.84	22.2
Subtotal	81.83	86.13	87.88	96.08	96.69	97.48	88.96	91.41	92.68
Agriculture									
Formal workers	3.1	3.05	2.73	0.67	0.7	0.53	1.89	1.88	1.63
Informal workers	6.85	4.62	3.72	1.55	0.88	0.56	4.2	2.75	2.14
Self-emp. workers	8.22	6.2	5.67	1.7	1.73	1.43	4.96	3.97	3.55
Subtotal	18.17	13.87	12.12	3.92	3.31	2.52	11.05	8.59	7.32

Note: formal workers are dependent employees with signed formal labour contracts, while informal workers do not have such labour contracts. Self-employed workers are independent workers that may or may not have legalized their activities.

Source: authors' compilation based on data from the PNAD (2003–4 and 2011–12) and PNADC (2018–19).

First, we can observe that the share of workers in non-agriculture activities is large in Brazil, around 90 per cent across all workers, and has increased continuously since 2003/04. Second, formal workers comprise almost half of the workforce. During the period of economic growth, their share in the non-agriculture sector went from 44.5 per cent in 2003/04 to 53.6 per cent in 2011/12. However, in the later period their share dropped to 50.8 per cent. The share of informal workers has decreased continuously since 2003/04, even during the recession. In part this was due to a considerable increase in the share of self-employed workers, which decreased during the boom between 2003/04 and 2011/12, and increased again after. The share of workers in the agricultural sector fell in all three categories between 2003 and 2019. Among them, self-employed workers have the largest share of employment, but they comprise less than 5 percent of the whole labour force across the entire period. For this reason, we do not exclude them from our main analysis.

Table 3 shows the evolution of employment across occupations defined at the one-digit level of ISCO-88. The occupational structure remained somewhat stable during the period, without considerable changes in most of the groups, apart from elementary occupations. The two professions with highest average wages, managers and professionals, had different trends in the period. Managers decreased in the share of employment, while professionals increased. The share of technicians and associated professionals expanded between 2003 and 2019. Hence, the three main occupational groups together increased their participation from around 19 per cent to 25 per cent, thus providing some evidence for polarization in employment at the upper end of occupations. Nonetheless, the pattern was not the same within subgroups.

Table 3: Share of employment by occupations

	Share of total employment (%)		
	2003/04	2011/12	2018/19
1 Managers	5.2	4.9	3.9
2 Professionals	6.8	9.3	11.4
3 Technicians and associated professionals	7.2	6.7	10.2
4 Clerical support workers	8.6	9.9	9.6
5 Services and sales workers	19.8	22.2	19.4
6 Skilled agr., forestry and fishery workers	5.2	3.7	6.0
7 Craft and related trades workers	16.9	18.0	20.3
8 Plant and mach. operators and assemblers	5.7	6.4	7.5
9 Elementary occupations	24.7	18.9	11.6

Note: occupations are classified following the one-digit ISCO-88 system.

Source: authors' compilation based on data from the PNAD (2003/04 and 2011/12) and PNADC (2018/19).

A similar mixed picture can be observed among occupations in the middle and bottom of the distribution. The share of employment of clerical support workers and services and sales remained more or less stable in both periods, together with skilled workers in agriculture and similar activities. Craft workers and plant and machine operators both incremented their share in total employment. Finally, elementary occupations, the group with the lowest average earnings, observed a considerable reduction in the share of employment. Hence, while there was some stability in the middle and an increase in some basic occupations, the large drop in the share of elementary occupations is probably related to demographic and educational changes in the country. In particular, the importance of this sector in total employment in Brazil and other developing countries may itself make it difficult to extrapolate polarization patterns from developed countries, as in those economies this group of workers is less important.

In Table 4 we observe the evolution of employment across different industries in Brazil. The first clear trend, already noticed in Table 2, is the fall of employment in agriculture. Manufacturing also continuously reduced its share of total employment, while construction expanded in the first period and contracted in the second.

Table 4: Distribution of workers by industry (%), 2003/04–2018/19

Industries	All workers		
	2003/04	2011/12	2018/19
Agriculture, livestock, forestry, fishing, and aquaculture	18.36	13.57	8.75
General manufacture	14.75	13.95	12.98
Construction	6.86	8.66	7.29
Trade and repair of motor vehicles and motorcycles	17.79	18.23	19.01
Accommodation and food	3.74	4.93	5.77
Transport, storage, and communication	11.68	14.33	16.50
Public administration, defence, and social security	4.93	5.41	5.49
Education, human health, and social services	8.91	9.47	12.12
Domestic services	8.75	7.43	6.69
Other services	3.92	3.90	5.36
Ill-defined activities	0.30	0.12	0.04

Note: sectors are classified following the Brazilian system (CNAE 2.0).

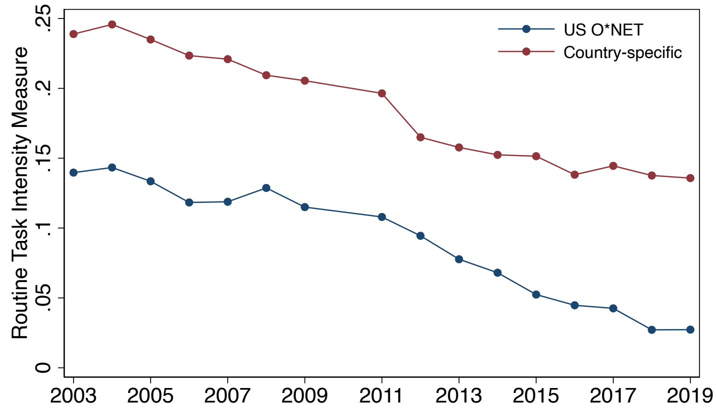
Source: authors' compilation based on data from the PNAD (2003/04 and 2011/12) and PNADC (2018/19).

The services sector incremented its share in total employment in both periods, a trend that has been in place in Brazil for a few decades now. In particular, transport, storage, and communications; accommodation and food; and educational and health services expanded quickly. These are precisely the sectors that in general are not routine-intensive and cannot be easily automated or offshored. They are also the ones more likely to benefit from technological advances in the past that may be linked with increases in productivity, computers in particular.

As we can see, changes in occupational and sectoral composition of the Brazilian economy in the last decades were not dramatic. Nonetheless, they likely have had an impact on the way production is organized and should be reflected in measures of RTI. Figure 5 shows how average RTI behaved in the period under analysis in Brazil. Workers are grouped into occupations at the two-digit ISCO-88 level, each of them with a corresponding RTI level. Occupations are then weighted by the total number of employees. We measure RTI using both the O*NET classification and the country-specific measure.

Both measures of average RTI in the economy show a reduction in the intensity of routine tasks in the period. This can be seen as evidence of either automation of tasks previously performed by workers or offshoring of such activities. Either way, this suggests a reduction in the supply of jobs that are routine-intensive and that have been traditionally linked to middle-class occupations, a pattern observed in developed countries that has been linked to polarization, as in Firpo et al. (2011).

Figure 5: Evolution of RTI (all occupations)

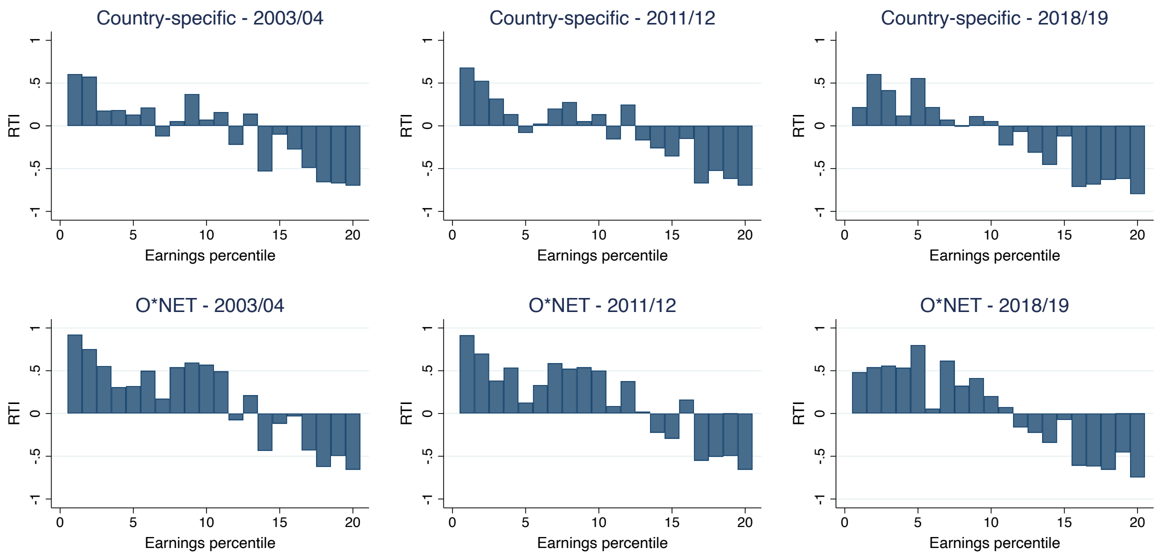


Note: workers are grouped in occupations defined at the two-digit ISCO-88 level. Average RTI levels for each year are computed weighing each occupation by the number of employees.

Source: authors' compilation based on data from the PNAD (2003–15) and the PNADC (2016–19).

Figure 6 shows how average RTI at the occupation level is associated with earnings; occupations are ranked by their average earnings in the initial period. Occupations with lower average earnings are also those that are more intense in routine tasks. This pattern is observed whether we measure RTI using O*NET or country-specific definitions. A small difference between these two measures is noticed when we consider occupations in the middle of the distribution. These occupations score higher in O*NET-measured RTI than in the country-specific measure in all years.

Figure 6: RTI by earnings percentile (demi-deciles), 2003/04–18/19



Note: individuals are grouped at two-digit ISCO-88 levels and occupations are ranked based on their 2003/04 average earnings.

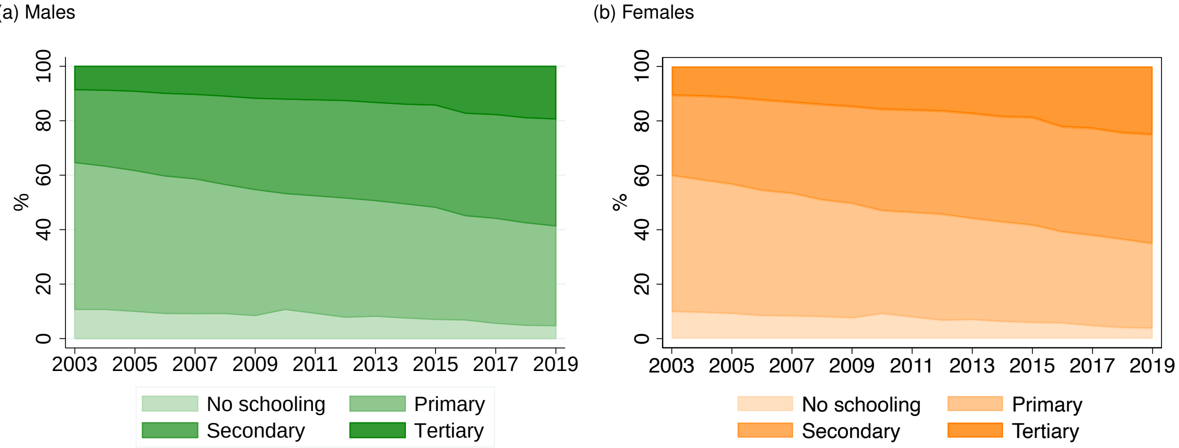
Source: authors' compilation based on data from the PNAD (2003/04 and 2011/12) and PNADC (2018/19).

In summary, the services sector has expanded in Brazil in the last decades, alongside a fall in employment in occupations that are intensive in routine tasks. There is a marked negative relationship between intensity of routine tasks in occupations and average earnings across Brazilian occupations.

4.3 Skill supply and education premium

Changes in the supply of skilled labour, here defined as an increase in average schooling of the workforce, has been pointed out as an important factor behind the reduction in inequality in Brazil (Barros et al. 2010). More recent research, however, highlights the dual role played by the expansion of educational levels. At the same time that a larger supply of skilled labour reduces education premia, higher education levels have an inequality-enhancing effect because of the convexity of returns to education (Alvarez et al. 2018; Ferreira et al. 2021; Haanwinckel 2018). Figure 7 shows that the number of workers holding tertiary and secondary degrees increased continuously in Brazil between 2003 and 2019.

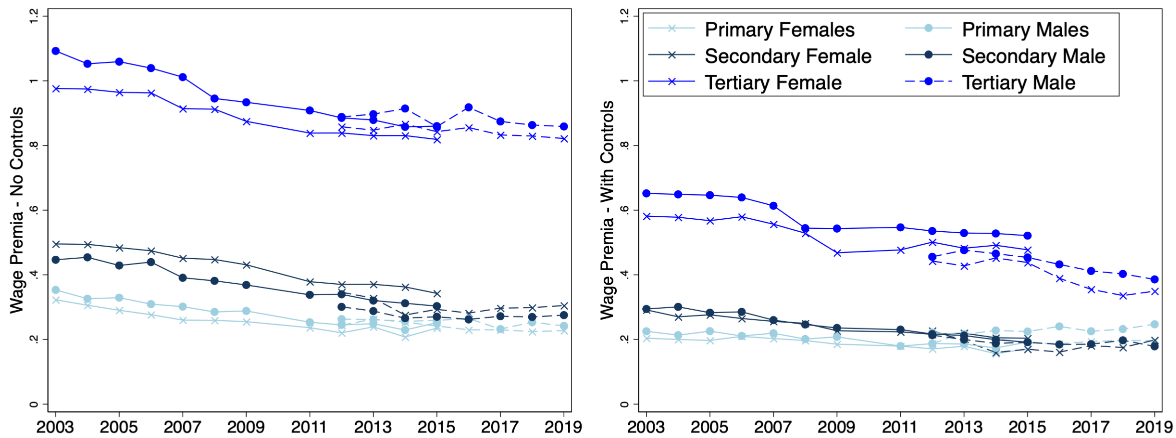
Figure 7: Supply of skills in the labour market for men and women (2003–19)



Source: authors' compilation based on data from PNAD (2003–15) and PNADC (2016–19).

The increase in the supply of skilled labour resulted in lower skill-premia. Figure 8 shows the evolution of the education wage premium in Brazil between 2003 and 2019, using as a comparison group workers without any schooling. Panel (a) displays wage premia without any control, while panel (b) includes controls for age (15–24, 25–44, and 45–64), race (Indigenous, White, Black, Asian descendent, and Brown), state, and two-digit ISCO-88 occupation. We observe large but decreasing wage premia for workers with tertiary education.

Figure 8: Education premium in Brazil



Note: education premium is estimated without controls as the ratio between average log earnings in the educational group of interest and average log earnings of individuals without formal schooling. Education premium with controls estimate Mincerian equations using four categories for education, with no formal schooling being the reference group. Controls are age, race, state, and two-digit occupation.

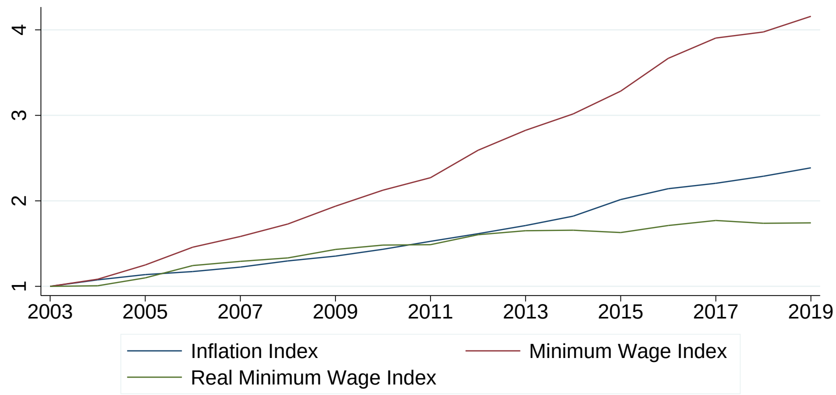
Source: authors' compilation based on data from the PNAD (2003–15) and PNADC (2012–19).

The wage premia for workers with primary and secondary education are much smaller and almost of the same size when we account for observable characteristics. They have also reduced in size since 2003, although to a much lesser extent then the wage premium for tertiary education.

4.4 Minimum wage

The minimum wage (MW) increased in real terms in Brazil during the period under analysis, as can be seen in Figure 9, especially between 2003 and 2012, when the real value of the MW more than doubled. Researchers have argued that the increase in MW is an important factor behind the drop in inequality observed in the period (Engbom and Moser 2021). This is so because the MW compressed the wage distribution at the same time that there was no significant negative effects on employment.

Figure 9: The evolution of the MW in Brazil



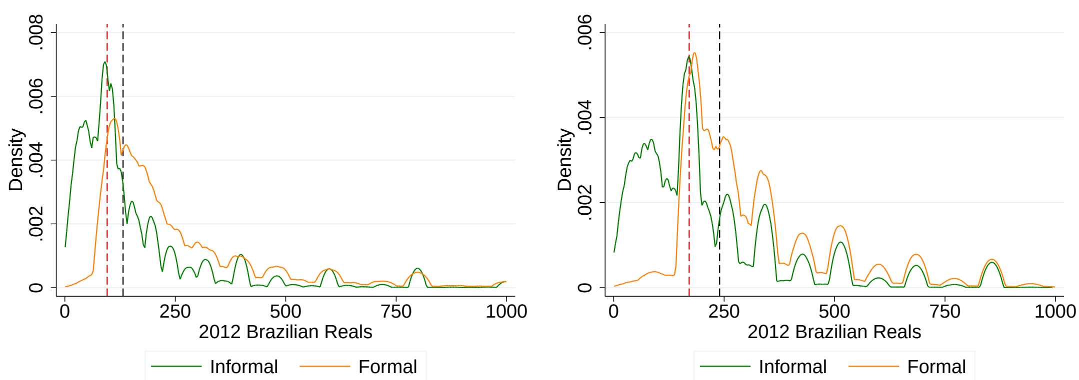
Note: the inflation index is the consumer price index (IPCA).

Source: authors' compilation based on data from the IPEA Data website.

The bite of the MW in Brazil is considerable and has a noticeable impact on the wage distribution of workers in both the formal and informal sectors. Figure 10 shows the distribution of wages for these workers in 2001 and 2019. It can be seen how the MW 'drags' the income distribution as its real value increases from 2001 to 2019. The inequality-decreasing effects of this are not small. In fact, Engbom and Moser (2021) estimate that around one-third of the observed 25.9 log-point reduction in the variance of log earnings inequality in Brazil between 1996 and 2012 can be attributed to MW increases.

Figure 10: The bite of the MW in the Brazilian wage distribution

(a) 2003 (b) 2019



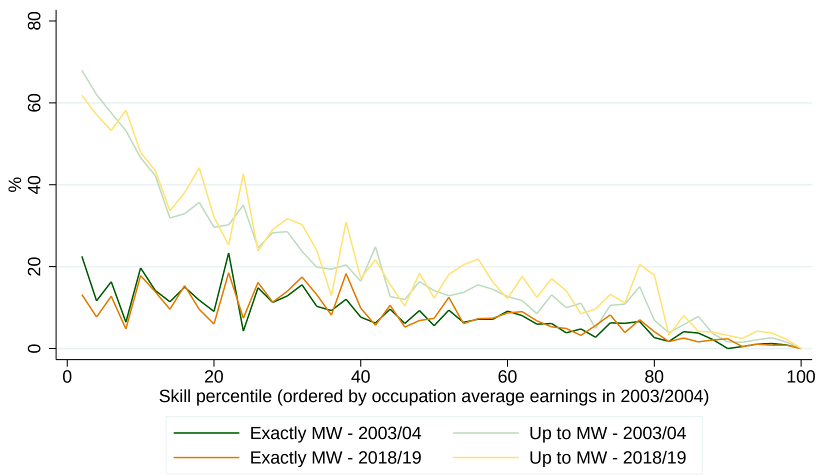
Note: the red dash lines mark the MW and the black dashed lines mark the median of the whole earnings distribution. Formal workers are dependent employees that hold signed labour contracts and self-employed workers that contribute to the INSS. Informal workers are dependent workers that do not have legal labour contracts or self-employed workers that do not contribute to the INSS. Kernel densities are estimated using the Epanechnikov function and Silverman's (1986) 'optimal' bandwidth.

Source: authors' compilation based on data from the PNAD (2003) and PNADC (2019).

Changes in the MW can have important effects not only on the wage distribution, but also on gaps across subgroups of the population. For instance, Derenoncourt and Montialoux (2021) show that MW increases in the United States had an important impact on racial gaps in earnings. The same effect is likely to be found in Brazil, and possibly across other subgroups of the population in which the MW bites differently, such as occupational groups.

Figure 11 shows that despite the large increase in the real MW between 2003 and 2019, the share of individuals receiving up to or exactly the MW within each occupation remained stable. As expected, the bindingness of the MW is higher in low-skilled occupations. Therefore, the rises in MW in the last decades should have contributed at least in part to reducing earnings gaps between occupations, everything else constant. However, we do not aim at disentangling this effect in this paper, although we believe future research should cover this topic in more detail.

Figure 11: The evolution of the MW in Brazil



Note: individuals are grouped at the three-digit ISCO-88 level and occupations are ranked based on their 2003/04 average earnings. 'Exactly MW' corresponds to the share of individuals in each occupational group that reports earning exactly the MW. 'Up to MW' corresponds to individuals that earn up to and exactly the MW.

Source: authors' compilation based on data from the PNAD (2003/04) and PNADC (2018/19).

5 The role of tasks and skills in changing earnings inequality

5.1 Job and earnings polarization

In this section we focus on evaluating employment and earnings polarization in Brazil, applying the methodology proposed by Goos and Manning (2007) and Sebastian (2018). Table 5 shows the results of regressions of changes in employment and mean earnings on lagged earnings and its square at the occupation level, following Equation 2. Polarization is characterized by a U-shaped relationship between changes in employment or earnings with respect to earnings in the initial period, which should be reflected in a positive coefficient for the square of occupations' mean log earning.

The results in Table 5 provide mixed support for the polarization hypothesis in terms of employment, but confirm this phenomenon with respect to earnings. In the first period we observe the opposite of polarization in the share of employment since the estimated coefficients suggest a concave relationship between growth in employment shares and earnings in the initial period, suggesting a larger growth in the middle of the distribution. In the second period, however, we find evidence of polarization as the square of initial earnings is positive and significant. Comparing 2018/19 with 2003/04 results in no significant coefficient, although the point estimates suggest a small polarization.

Table 5: OLS regressions for job and earnings polarization

	Log change in employment share			Change in log mean earnings		
	(1) 2003/04– 2011/12	(2) 2011/12– 2018/19	(3) 2003/04– 2018/19	(4) 2003/04– 2011/12	(5) 2011/12– 2018/19	(6) 2003/04– 2018/19
(Log) mean earnings ($t-1$)	1.069**	–2.722**	–0.909	–0.631***	–2.625***	–2.384***
	(0.407)	(1.344)	(1.054)	(0.117)	(0.735)	(0.512)
Sq. (log) mean earnings ($t-1$)	–0.084**	0.224*	0.086	0.044***	0.207***	0.189***
	(0.039)	(0.117)	(0.099)	(0.011)	(0.062)	(0.046)
Constant	–3.294***	8.074**	2.237	2.409***	8.270***	7.706***
	(1.026)	(3.815)	(2.741)	(0.300)	(2.178)	(1.417)
Observations	78	78	78	78	78	78
Adjusted R^2	0.179	0.059	–0.015	0.647	0.422	0.669

Note: this table presents formal estimates on the quadratic fit following Equation 2. Columns 1–3 (4–6) are for ordinary least squares estimates for the change in the logarithm of employment share (the logarithm of mean earnings) on initial log mean hourly earnings and its square using the three-digit level ISCO-88 occupations. Occupations are weighted by their initial employment share. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: authors' calculations.

All estimated coefficients are significant for the relationship between changes in mean earnings and support the conclusion of polarization. The magnitude of the phenomenon, however, is weaker between 2003 and 2012, being mostly driven by changes in earnings between 2012 and 2019.

In a similar way, Table 6 shows how changes in employment and average earnings at the occupation level are associated with RTI, as in Equation 3, thus evaluating the polarization argument with respect to the task content of occupations. We run regressions using RTI measured based on both O*NET and country-specific information.

Again, we find mixed evidence of polarization with respect to employment, but average earnings display some polarization, especially in the latter period. Results are similar whether we use the O*NET or country-specific RTI definitions, although they are in general imprecise. The estimated coefficients are only significant for changes in employment observed between 2003 and 2012 using the country-specific RTI (panel B) and suggest the opposite conclusion of polarization, just like in the regression using earnings instead of RTI. The point estimate using the O*NET classification is also negative, but not significant. Using data from other periods, we find no evidence of polarization. When we consider average earnings, in columns 4–6, the point estimates all suggest polarization using both measures, although the precision is small. As in Table 5, polarization seems much stronger in the second period than the first.

To further appraise the polarization argument, Figure 12 shows how changes in employment shares and average earnings depend on an occupation's skill, ordered according to average occupational earnings in 2003/04. Changes in employment are noisy, and it is difficult to observe any patterns.

Changes in average earnings, however, show a clearer pattern. In the first period, we observe larger increases in average earnings among the least qualified occupations, in line with Figure 4. However, there is a clear change in the second period, where gains in earnings are larger in the most qualified occupations.

Table 6: Regression model on the relationship between RTI and the occupation and earning

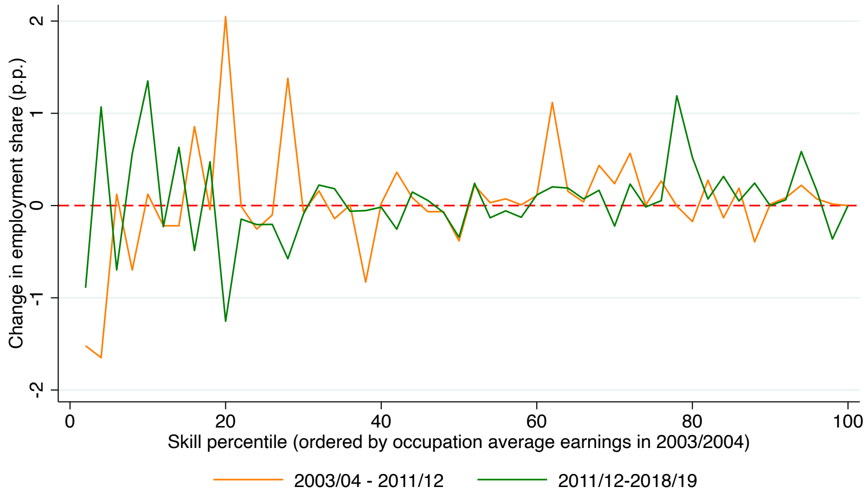
	Log change in employment share			Change in log mean earnings		
	(1) 2003/04–2011/12	(2) 2011/12–2018/19	(3) 2003/04–2018/19	(4) 2003/04-2011/12	(5) 2011/12–2018/19	(6) 2003/04–2018/19
*Panel A: O*NET measures*						
O*NET RTI	–0.149*	0.034	–0.050	0.153***	0.027	0.180***
	(0.075)	(0.104)	(0.122)	(0.024)	(0.049)	(0.061)
Sq. O*NET RTI	–0.161	0.366	0.067	0.128**	0.277	0.405
	(0.257)	(0.256)	(0.306)	(0.056)	(0.228)	(0.265)
Constant	0.141	–0.229*	–0.122	0.227***	0.038	0.264***
	(0.122)	(0.121)	(0.166)	(0.022)	(0.086)	(0.092)
Observations	78	78	78	78	78	78
Adjusted R^2	0.019	0.045	–0.025	0.540	0.118	0.317
Panel B: country-specific measures						
RTI	–0.161**	–0.028	–0.189	0.168***	0.127	0.296***
	(0.075)	(0.141)	(0.166)	(0.030)	(0.079)	(0.090)
Sq. RTI	–0.310**	0.110	–0.199	0.080	0.431**	0.510*
	(0.139)	(0.285)	(0.285)	(0.084)	(0.195)	(0.258)
Constant	0.083	–0.096	–0.014	0.273***	0.006	0.278***
	(0.063)	(0.065)	(0.086)	(0.027)	(0.033)	(0.049)
Observations	78	78	78	78	78	78
Adjusted R^2	0.182	–0.024	0.017	0.387	0.282	0.430

Note: this table presents formal estimates on the quadratic fit following Equation 3. Columns 1–3 (4–6) are for ordinary least squares estimates for the change in the logarithm of employment share (the logarithm of mean earnings) on RTI and its square using the three-digit level ISCO-88 occupations. Occupations are weighted by their initial employment share. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

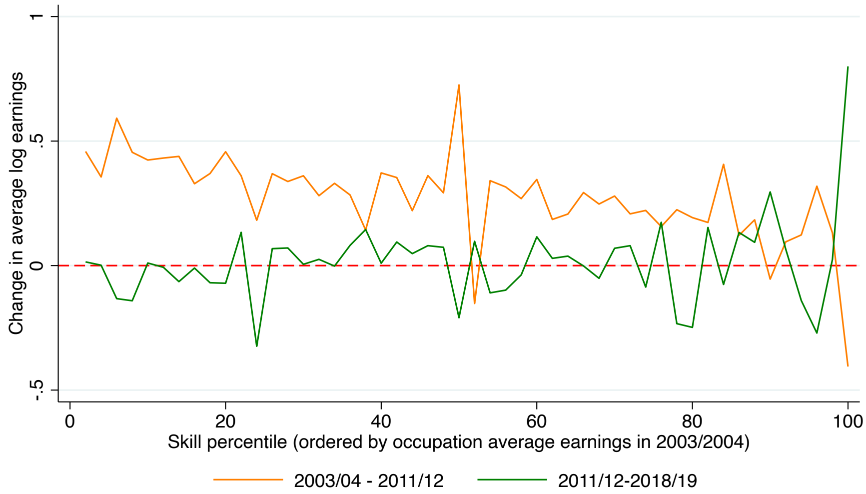
Source: authors' calculations.

Figure 12: Change in employment and earnings across skill percentiles

(a) Employment



(b) Earnings



Note: individuals are grouped by three-digit level ISCO-88 occupations, and occupations are ranked based on their 2003/04 average earnings.

Source: authors' compilation based on data from the PNAD (2003/04 and 2011/12) and PNADC (2018/19).

Figure 12 suggests that rather than polarization, the estimated coefficients are detecting larger growth rates in the most qualified occupations in the second period, and a drop in employment in the bottom occupations that was mostly compensated by increases in the 20th to 40th percentiles in the first period. The pattern that most resembles polarization is in employment shares in the second period. The data are noisy, however, and this is reflected in the large standard errors shown in Table 5.

5.2 Earnings inequality across occupations and its relationship to RTI

To evaluate the importance of occupations in earnings inequality, we first conduct a Shapley decomposition of the Gini index, as in Equation 4. Table 7 shows the results of this decomposition for all three periods under analysis. Nearly half of the Gini index is accounted for by differences in earnings across occupations in 2003/04. This share decreases to around 40 per cent in the later period, meaning that most of inequality is explained by differences in earnings observed between individuals in the same occupations. Occupations play a more important role in accounting for inequality in Brazil than in Argentina or Ghana (Gradín and Schotte 2020; Maurizio and Monsalvo 2021).

Table 7: Gini index decomposed into inequality between and within occupations

	Actual			Shares constant			Means constant		
	2003/04	2011/12	2018/19	2003/04	2011/12	2018/19	2003/04	2011/12	2018/19
Overall Gini (G)	0.547	0.495	0.493	0.547	0.501	0.518	0.547	0.522	0.512
Between-occupation (B)	0.261	0.223	0.196	0.261	0.217	0.213	0.261	0.242	0.202
% (B/G)	47.7	45.0	39.7	47.7	43.3	41.1	47.68	46.3	39.45
Within-occupation (W)	0.286	0.272	0.298	0.286	0.284	0.305	0.286	0.281	0.31
% (W/G)	52.3	55	60.3	52.3	56.7	58.9	52.3	53.7	60.5

Note: the decomposition follows the Shapley methodology explained in Equation 4, using as reference groups occupations defined at the ISCO-88 two-digit level. 'Shares constant' reweights the sample so the share of employment across occupations is the same as the one observed in 2003/04, while 'means constant' rescales earnings within occupations so average earnings of each occupation are the same as those observed in 2003/04.

Source: authors' compilation based on data from the PNAD (2003/04 and 2011/12) and PNADC (2018/19).

The observed change in the shares attributed to between and within occupations can change either because of changes in the composition of employment or because of changes in average returns of these occupations. When we hold the share of employment of each occupation the same as that observed in the first period, the share of the Gini index resulting from differences between and within occupations remains almost the same. We obtain a similar result when we hold average occupation earnings constant at their 2003/04 levels.

Table 8 further decomposes the between-occupation component of the Gini, as measured in Table 7, into a part attributed to changes in the average occupational wages and changes in the share of employment across these occupations, following Equation 6. In the first period, the between-occupation component is mostly explained by changes in mean earnings, while in the second period changes are driven mostly by employment composition. Across the whole period, both changes in mean earnings across occupations and the share of employment of each occupation contributed to reduced inequality, with changes in employment composition explaining a larger part of it.

Table 8: Change in the Gini index decomposed into the contribution of changes in employment shares and in mean earnings

	2003/04–2011/12	2011/12–2018/19	2003/04-2018/19
Change in employment shares (mean earnings constant)	–0.0065	–0.0315	–0.038
Change in mean earnings (employment shares constant)	–0.0315	0.0045	–0.027
Total change	–0.038	–0.027	–0.065

Note: estimates are based on those reported in Table 7, applying the decomposition described in Equation 6.

Source: authors' calculations.

Table 9 shows the concentration index measuring inequality based on the ranking of occupation using RTI, comparing it with the Gini index between occupations. Recall that when the ratios between these two measures are similar it means that the ranking of occupations by earnings and by RTI are alike. This suggests that the intensity of routine tasks is an important component in determining differences in earnings between occupations, rather than other factors such as skills. In Brazil, the concentration index using RTI is around 90 per cent of the Gini between occupations, pointing to the importance of routine tasks in explaining earnings differences between occupations. The conclusion is the same whether we use country-specific measures or O*NET, and reflects the patterns uncovered in Table 6, where we observe a large negative association between RTI and average earnings across occupations.

Table 9: Concentration index based on RTI and Gini index between occupations

	Actual			Shares constant			Means constant		
	2003/04	2011/12	2018/19	2003/04	2011/12	2018/19	2003/04	2011/12	2018/19
Gini between occupations (B)	0.404	0.332	0.324	0.404	0.348	0.327	0.404	0.396	0.383
Concentration index									
RTI (country-specific) (C)	0.384	0.311	0.292	0.384	0.331	0.292	0.384	0.354	0.339
% (C/B)	94.9	93.6	90.3	94.9	95	89.3	94.9	89.4	88.6
RTI (O*NET) (O)	0.384	0.31	0.306	0.384	0.327	0.315	0.384	0.357	0.343
% (O/B)	95.1	93.2	94.5	95.1	93.8	96.2	95.1	90.1	89.6

Note: the Gini and concentration indices are estimated by replacing individuals' earnings by the average of their occupation, using as reference groups occupations defined at the ISCO-88 two-digit level. 'Shares constant' reweights the sample so the share of employment across occupations is the same as the one observed in 2003/04, while 'means constant' rescales earnings within occupations so average earnings of each occupation are the same as those observed in 2003/04.

Source: authors' compilation based on data from the PNAD (2003/04 and 2011/12) and PNADC (2018/19).

5.3 Disentangling inequality drivers: the RIF regression decomposition

As our last exercise, we use RIF regressions to assess the role of changes in the structure of earnings and workers' characteristics in accounting for observed changes in inequality, and the role of changes in RTI in particular. Table 10 shows the results of Gini decomposition using the traditional OB decomposition, without reweighting, as in Equation 10.

We observe that the bulk of changes in the first period are accounted for by changes in the structure of earnings, corresponding to a drop of 6 Gini points in the period between 2003/04 and 2011/12. Changes in worker composition would have increased inequality if there were no change in earnings structure. In the second period, between 2011/12 and 2018/19, there was a small rise in inequality. Composition effects drive this increase, which would have been larger if it was not for an inequality-reducing structure effect. Across the whole period, between 2003/04 and 2018/09, there was a small decrease in inequality, brought about by a large compressing effect in the structural component that was partially counteracted by changes in worker composition. The results are the same whether we use O*NET or country-specific RTI.

The detailed decomposition shows that the increase in education drives most of the increase in inequality, at the same time that changes in the returns to education led to a significant reduction in inequality that is almost the same size as the composition effect. This finding is similar to Ferreira et al. (2021), related to the 'paradox of progress'. Other factors play a minor role, although one can highlight changes in racial gaps and formality as important ones.

With respect to RTI itself, we observe similar results whether we use O*NET or country-specific measures when we look at composition effects. Both measures show a small compression from composition effect in the first period and a larger inequality-enhancing effect in the later period that dominates when we analyse changes in the whole period. However, results are distinct when we look at changes in the structure. The country-specific RTI structural effects are not significant apart from for the whole period, when it contributed to a slight reduction in inequality. The O*NET measures have much larger impacts on inequality, corresponding to a large decrease in the first and a large increase in the last period that compensate for each other when we consider changes between 2003/04 and 2018/19.

To validate our previous analysis we also consider the reweighting approach, as described in Equation 13. The results are in Table 11. When we consider the aggregated decomposition, we reach similar conclusions as before. Changes in pure structure are responsible for most of the reduction in inequality in the first period, while changes in composition dominate the increase in inequality in the second. However, we observe relatively large specification errors, which are possibly due to failures of our linearity assumption coupled with large changes in worker composition.

Table 10: RIF decomposition of Gini (× 100), without reweighting

	Country-specific RTI			O*NET RTI		
	(1) 2003–11	(2) 2011–18	(3) 2003–18	(4) 2003–11	(5) 2011–18	(6) 2003–18
Gini, period 1	44.72***	46.94***	46.94***	44.72***	46.94***	46.94***
	(0.14)	(0.18)	(0.18)	(0.14)	(0.18)	(0.18)
Gini, period 2	49.76***	44.72***	49.76***	49.76***	44.72***	49.76***
	(0.10)	(0.14)	(0.10)	(0.10)	(0.14)	(0.10)
Gini, difference	–5.04***	2.22***	–2.82***	–5.04***	2.22***	–2.82***
	(0.16)	(0.24)	(0.21)	(0.16)	(0.24)	(0.21)
Composition	1.17***	3.96***	6.37***	1.01***	4.01***	6.37***
	(0.09)	(0.10)	(0.16)	(0.09)	(0.10)	(0.16)
Structure	–6.21***	–1.73***	–9.19***	–6.05***	–1.78***	–9.19***
	(0.17)	(0.28)	(0.26)	(0.17)	(0.28)	(0.26)
Composition effects						
Education	1.87***	2.80***	5.76***	1.72***	2.55***	5.49***
	(0.08)	(0.08)	(0.15)	(0.08)	(0.07)	(0.14)
Age	0.18***	0.26***	0.35***	0.17***	0.26***	0.33***
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Gender	–0.05***	–0.10***	–0.13***	–0.04***	–0.08***	–0.12***
	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)
Race	0.07***	–0.03***	0.12***	0.08***	–0.02*	0.14***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Formality	–0.75***	0.58***	–0.10*	–0.81***	0.59***	–0.14**
	(0.03)	(0.05)	(0.05)	(0.03)	(0.05)	(0.05)
RTI	–0.16***	0.44***	0.37***	–0.10***	0.71***	0.68***
	(0.02)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Structure effects						
Education	–2.80***	–2.30***	–6.19***	–2.93***	–2.33***	–6.48***
	(0.28)	(0.29)	(0.35)	(0.28)	(0.29)	(0.35)
Age	0.41**	0.10	0.60***	0.38**	0.14	0.61***
	(0.17)	(0.25)	(0.22)	(0.17)	(0.25)	(0.22)
Gender	–0.22	–0.08	–0.30	–0.10	–0.11	–0.21
	(0.14)	(0.22)	(0.20)	(0.14)	(0.21)	(0.19)
Race	–1.22***	–0.38*	–1.69***	–1.18***	–0.40*	–1.65***
	(0.14)	(0.21)	(0.18)	(0.14)	(0.21)	(0.18)
Formality	0.25	–1.11***	–0.93***	0.26	–1.39***	–1.21***
	(0.17)	(0.27)	(0.24)	(0.17)	(0.27)	(0.24)
RTI	–0.21	–0.07	–0.37**	–1.10***	1.25***	0.09
	(0.14)	(0.18)	(0.17)	(0.12)	(0.15)	(0.13)
Constant	–2.42***	2.11***	–0.31	–1.39***	1.06**	–0.33
	(0.39)	(0.48)	(0.47)	(0.43)	(0.49)	(0.50)
Observations	603,128	651,485	655,261	603,128	651,485	655,261

Note: the years 2003, 2011, and 2018 also include data from 2004, 2012, and 2019, respectively. The table reports full results for RIF decompositions of the Gini, without reweighting. For details on the decomposition, see Equation 13. Bootstrap standard errors with 100 replications in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' compilation based on data from the PNAD (2003/2004 and 2011/2012) and PNADC (2018/20190).

Table 11: RIF decomposition of Gini ($\times$ 100), with reweighting

	Country-specific RTI			O*NET RTI		
	(1) 2003–11	(2) 2011–18	(3) 2003–18	(4) 2003–11	(5) 2011–18	(6) 2003–18
Gini, period 1	44.72***	46.94***	46.94***	44.72***	46.94***	46.94***
	(0.14)	(0.21)	(0.21)	(0.14)	(0.21)	(0.21)
Gini, period 2	49.76***	44.72***	49.76***	49.76***	44.72***	49.76***
	(0.11)	(0.14)	(0.11)	(0.11)	(0.14)	(0.11)
Gini, difference	–5.04***	2.22***	–2.82***	–5.04***	2.22***	–2.82***
	(0.17)	(0.25)	(0.24)	(0.17)	(0.25)	(0.24)
Composition	0.02	2.46***	1.87***	–0.08	2.45***	1.89***
	(0.06)	(0.09)	(0.12)	(0.06)	(0.09)	(0.12)
Pure composition	1.16***	4.05***	6.74***	1.03***	4.05***	6.70***
	(0.08)	(0.10)	(0.18)	(0.08)	(0.10)	(0.17)
Specif. error	–1.14***	–1.59***	–4.86***	–1.11***	–1.60***	–4.80***
	(0.05)	(0.05)	(0.11)	(0.05)	(0.05)	(0.11)
Structure	–5.06***	–0.24	–4.69***	–4.96***	–0.23	–4.71***
	(0.16)	(0.25)	(0.25)	(0.16)	(0.25)	(0.25)
Rewgt. error	0.02**	–0.06***	–0.09***	–0.00	–0.01	–0.07***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Pure structure	–5.08***	–0.18	–4.60***	–4.95***	–0.22	–4.64***
	(0.16)	(0.25)	(0.25)	(0.16)	(0.25)	(0.24)
Pure composition effects						
Education	1.87***	2.88***	6.05***	1.73***	2.64***	5.77***
	(0.06)	(0.07)	(0.15)	(0.05)	(0.07)	(0.14)
Age	0.18***	0.28***	0.37***	0.17***	0.27***	0.34***
	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)
Gender	–0.05***	–0.09***	–0.12***	–0.04***	–0.09***	–0.12***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Race	0.07***	–0.02**	0.15***	0.08***	–0.01	0.17***
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)	(0.03)
Formality	–0.73***	0.60***	0.01	–0.80***	0.58***	–0.05
	(0.03)	(0.05)	(0.06)	(0.03)	(0.05)	(0.06)
RTI	–0.19***	0.41***	0.27***	–0.11***	0.67***	0.59***
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)
Pure structure effects						
Education	0.06	1.05***	1.63***	–0.04	1.09***	1.43***
	(0.26)	(0.38)	(0.25)	(0.25)	(0.37)	(0.26)
Age	0.59***	0.08	0.98***	0.57***	0.16	1.03***
	(0.16)	(0.26)	(0.23)	(0.16)	(0.25)	(0.23)
Gender	–0.21	–0.48**	–0.75***	–0.12	–0.50**	–0.71***
	(0.16)	(0.23)	(0.24)	(0.15)	(0.23)	(0.23)
Race	–1.10***	–0.13	–1.85***	–1.03***	–0.13	–1.75***
	(0.16)	(0.23)	(0.26)	(0.16)	(0.23)	(0.26)
Formality	0.67***	0.20	0.70***	0.68***	–0.11	0.40
	(0.18)	(0.30)	(0.27)	(0.18)	(0.29)	(0.26)
RTI	–0.17	0.17	0.28*	–1.44***	0.98***	–0.43**
	(0.13)	(0.19)	(0.16)	(0.12)	(0.15)	(0.17)
Constant	–4.93***	–1.07**	–5.59***	–3.58***	–1.71***	–4.61***
	(0.42)	(0.49)	(0.49)	(0.43)	(0.48)	(0.53)
Observations	603128	651485	655261	603128	651485	655261

Note: the years 2003, 2011, and 2018 also include data from 2004, 2012, and 2019, respectively. The table reports full results for RIF decompositions of the Gini, using reweighting. For details on the decomposition, see Equation 13. Bootstrap standard errors with 100 replications in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' compilation based on data from the PNAD (2003/2004 and 2011/2012) and PNADC (2018/2019).

As before, changes in average schooling dominate the pure composition effects, resulting in increases in inequality. However, we do not observe the same effect as before for education in pure structure effects. Rather, this effect is null or positive. The negative structure effect of education observed in Table 10 is actually driven by specification errors, as can be seen in Table A2 in Appendix A, which displays the full results of our reweighting methodology.

With respect to changes attributed to the RTI, we again observe similar conclusions as before. The estimates of the pure composition effect are similar either using O*NET or country-specific measures, showing a small compression effect in the first period and a larger inequality-enhancing effect in the second. Pure structural effects are only detected using the O*NET measure and point towards a large reduction in the first period and a smaller increase in the second. For the country-specific measure, changes in the return to RTI contributed to an increase in inequality between 2003/04 and 2018/19, although it is not significant in each sub-period.

As further robustness checks on our results, we replicate the work of Ferreira et al. (2021) for the period between 2002 and 2012. Table A1 contains a replication of their analysis in column 1, and columns 2 and 3 include RTI in their specification.[10] Our estimates are similar to theirs, although not exactly. One major difference is that we do not observe the same compression effect of potential experience. This difference, however, is possibly due to two reasons. First, they use potential experience,[11] whereas we simply use age. Second, we include age as three categories, while they use a rich quadratic term for potential experience.

Most interesting, however, is that the estimated composition and structural effects in their paper are similar to ours when we include RTI, with composition effects contributing slightly to increasing inequality and structure effects contributing to a larger extent to reducing it, especially using the O*NET definition. It is important to note that the inclusion of RTI has the effect of reducing the relative importance of education as a driver in the inequality reduction.

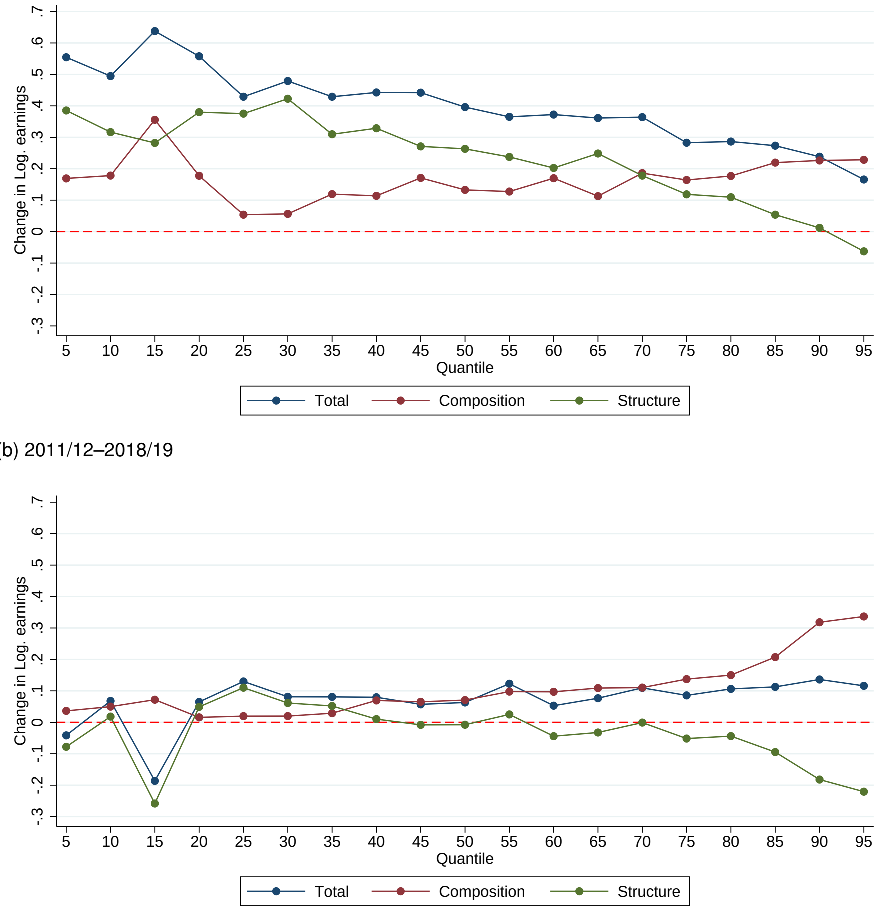
Table A3 further extends the analysis of Ferreira et al. (2021) by conducting a reweighted decomposition. The results are similar to before, although the effect of pure structure changes in RTI are much larger and counterbalanced by specification error, especially using country-specific RTI. We further note that when we apply the reweighting methodology to their specification, we find large positive pure structure effects for both education and potential experience that become negative when we include the specification error. This provides further evidence that changes in the composition of workers are indirectly responsible for changes in the earnings structure in the period, something that has been highlighted by structural estimations by Haanwinckel (2018), among others.

Figure 13 shows the results of the aggregate decomposition across several percentiles, without reweighting. In Appendix A Figure A1 shows the same results using the reweighted methodology with similar results. In the first period, we see that workers in all positions of the earnings distribution had increases in wages, but the benefits were larger at the bottom. Structure effects benefited mostly the bottom too, decreasing in size and eventually becoming negative for the very top. Composition effects were positive throughout the distribution, but especially in the bottom and top of the distribution.

[10] We do not replicate exactly their results because of small differences in the final samples and in the definition of a few variables. However, the conclusions we arrive at here are very similar to theirs.

[11] Defined as age minus years of schooling minus 6.

Figure 13: Aggregate decomposition by quantile, without reweighting
(a) 2003/04–2011/12



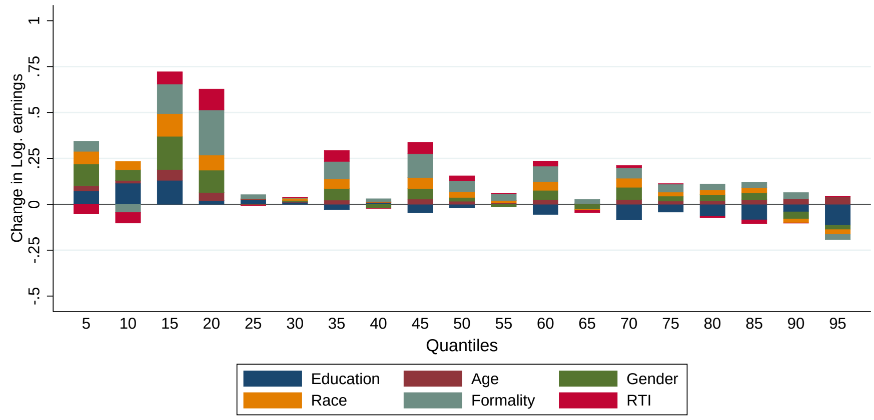
Note: these figures plot the changes in log earnings observed for the 5th to 95th quantiles, as well as the aggregated composition and structure effects estimated using RIF decompositions without reweighting (see Equation 10).
Source: authors' compilation based on data from the PNAD (2003/04 and 2011/2012) and PNADC (2018/19).

For the period between 2011/12 and 2018/19, however, the picture is much different. The bottom suffered losses that were driven mostly by changes in structure. The rest of the distribution had small gains. Interestingly, the top 20 per cent observed two conflicting tendencies. On the one hand, composition effects contributed to increased earnings. On the other, structure effects reduced earnings significantly. On net, their gains were similar to the middle of the distribution.

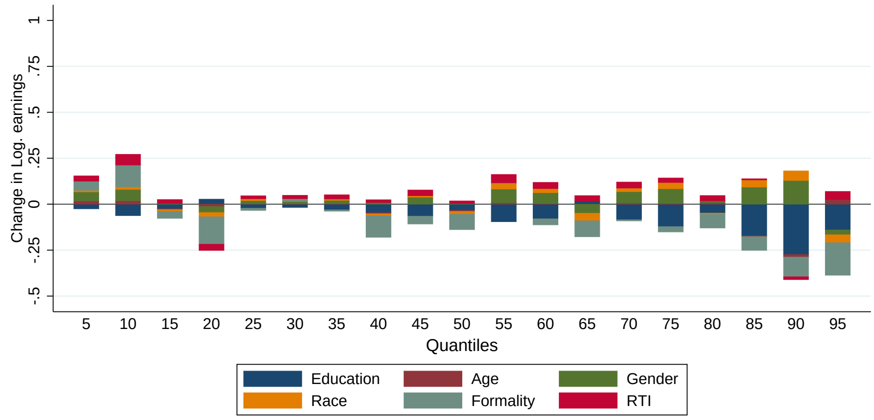
Figure 14 shows the results of a detailed decomposition of the structural effect using the RIF methodology without reweighting.[12] The results with reweighting are displayed in Figure A2. We observe large positive structural effects in the bottom of the distribution, driven mostly by changes in formality, gender and racial gaps, and even education. RTI contributed negatively to the bottom 10 per cent but positively to the 15th to the 70th percentiles.

[12] Results without the reweighting procedure could be interpreted as 'reduced form' ones and are more straightforward to interpret. Moreover, they also can be seen as an extension to other distributional parameters of the OB decomposition method.

Figure 14: Detailed decomposition by quantile, structural effects, without reweighting
(a) 2003–12



(b) 2012–19



Note: these figures plot the contribution of each factor to changes in log earnings observed for the 5th to 95th quantiles, based on the detailed decomposition of structural effects. The decomposition relies on RIF regressions without reweighting (see Equation 10).

Source: authors' compilation based on data from the PNAD (2003/04 and 2011/2012) and PNADC (2018/19).

In the period between 2011/12 and 2018/19 we see much smaller structural effects. The very bottom observe gains that are driven mostly by formality and RTI, although the benefits of formality become negative after. This is possibly related to a reduction in the gap between formal and informal workers. The RTI, however, has benefits throughout the wage distribution, with a few exceptions. The negative effects of changes in the return to education are mostly seen in the top of the distribution, as expected by the reduction in the return to schooling.

Figure A2 shows the same method using reweighting. The results for both periods are qualitatively similar, but are smaller in the first period and larger in the second. This is probably due to the role played by specification errors, which played an important role in our decomposition exercise.

6 Conclusion

This paper investigates the role that occupations and their task content in explaining trends in labour market polarization and earnings inequality in Brazil. We use information on country-specific job task content to construct measures of RTI. We show that this measure is highly correlated with average earnings across occupations and that changes in the Brazilian economy led to a decline in average RTI between 2003 and 2019.

We do not find evidence of employment polarization in the period, and polarization in earnings is more associated with a considerable pro-poor growth between 2003 and 2012 and pro-rich growth between 2012 and 2019. This was reflected in overall earnings inequality, which declined in the first period but marginally increased in the second.

Decomposition exercises show that the drop in inequality observed in the first period is mainly attributed to changes in the earnings structure, particular associated with large declines in the education premium. In the second period, composition effects dominated and resulted in increased inequality. The main driver is again education. The routine task content of occupations helps to account for part of the change in inequality, although to a much smaller extent. In particular, the reduction in average RTI increased inequality, while changes in its return had mixed effects in the period, decreasing inequality in the first period and reducing it in the second. Moreover, changes in RTI reduce the overall contribution of education to inequality, although this factor remains highly significant after accounting for the occupation's routine task content.

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A1 Appendix A: detailed results

Table A1: RIF decomposition of Gini (× 100), 2002/03–2011/12: Ferreira et al. (2021) specification

	No RTI	Country-specific RTI	O*NET RTI
	(1)	(2)	(3)
Gini, period 1	40.81***	40.81***	40.81***
	(0.07)	(0.07)	(0.07)
Gini, period 2	46.60***	46.60***	46.60***
	(0.07)	(0.07)	(0.07)
Gini, difference	–5.79***	–5.79***	–5.79***
	(0.11)	(0.11)	(0.11)
Composition	1.41***	1.13***	1.05***
	(0.07)	(0.07)	(0.07)
Structure	–7.20***	–6.92***	–6.85***
	(0.10)	(0.10)	(0.10)
Composition effects			
Education	3.00***	2.41***	2.36***
	(0.06)	(0.06)	(0.06)
Experience	–0.13***	–0.12***	–0.12***
	(0.01)	(0.01)	(0.01)
Formality	–0.98***	–0.93***	–0.95***
	(0.02)	(0.02)	(0.02)
Demography	–0.06***	–0.04***	–0.03***
	(0.01)	(0.01)	(0.01)
Region	–0.10***	–0.11***	–0.11***
	(0.01)	(0.01)	(0.01)
Sector	–0.33***	–0.13***	–0.24***
	(0.02)	(0.02)	(0.02)
RTI		0.05**	0.14***
		(0.02)	(0.02)
Structure effects			
Education	–1.47***	–1.19***	–1.17***
	(0.32)	(0.32)	(0.32)
Experience	–2.49***	–2.54***	–2.45***
	(0.44)	(0.44)	(0.44)
Formality	–0.11	–0.14	–0.18*
	(0.09)	(0.09)	(0.09)
Demography	–0.61***	–0.46**	–0.49***
	(0.18)	(0.18)	(0.18)
Region	–0.78***	–0.82***	–0.82***
	(0.24)	(0.25)	(0.25)
Sector	0.14	0.19	0.33
	(0.46)	(0.44)	(0.44)
RTI		–0.26**	–0.99***
		(0.12)	(0.11)
Constant	–1.87**	–1.70**	–1.07
	(0.75)	(0.71)	(0.73)
Observations	534,979	534,979	534,979

Note: the table reports full results for RIF decompositions of the Gini, using reweighting. For details on the decomposition, see Equation 10. Bootstrap standard errors with 100 replications in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Source: authors' compilation based on data from the PNAD (2002/03 and 2011/12).

Table A2: RIF decomposition of Gini ($\times$ 100), with reweighting: complete results

	Country-specific RTI						O*NET RTI					
	(1) 2003–11		(2) 2011–18		(3) 2003–18		(4) 2003–11		(5) 2011–18		(6) 2003–18	
Gini, period 1	44.72***	(0.14)	46.94***	(0.21)	46.94***	(0.21)	44.72***	(0.14)	46.94***	(0.21)	46.94***	(0.21)
Counterfactual	49.78***	(0.12)	47.18***	(0.18)	51.63***	(0.17)	49.67***	(0.12)	47.17***	(0.17)	51.65***	(0.17)
Gini, period 2	49.76***	(0.11)	44.72***	(0.14)	49.76***	(0.11)	49.76***	(0.11)	44.72***	(0.14)	49.76***	(0.11)
Difference	–5.04***	(0.17)	2.22***	(0.25)	–2.82***	(0.24)	–5.04***	(0.17)	2.22***	(0.25)	–2.82***	(0.24)
Total composition	0.02	(0.06)	2.46***	(0.09)	1.87***	(0.12)	–0.08	(0.06)	2.45***	(0.09)	1.89***	(0.12)
Pure composition	1.16***	(0.08)	4.05***	(0.10)	6.74***	(0.18)	1.03***	(0.08)	4.05***	(0.10)	6.70***	(0.17)
Specif. error	–1.14***	(0.05)	–1.59***	(0.05)	–4.86***	(0.11)	–1.11***	(0.05)	–1.60***	(0.05)	–4.80***	(0.11)
Total structure	–5.06***	(0.16)	–0.24	(0.25)	–4.69***	(0.25)	–4.96***	(0.16)	–0.23	(0.25)	–4.71***	(0.25)
Rwg. error	0.02**	(0.01)	–0.06***	(0.01)	–0.09***	(0.02)	–0.00	(0.01)	–0.01	(0.01)	–0.07***	(0.02)
Pure structure	–5.08***	(0.16)	–0.18	(0.25)	–4.60***	(0.25)	–4.95***	(0.16)	–0.22	(0.25)	–4.64***	(0.24)
Pure composition effects												
Education	1.87***	(0.06)	2.88***	(0.07)	6.05***	(0.15)	1.73***	(0.05)	2.64***	(0.07)	5.77***	(0.14)
Age	0.18***	(0.01)	0.28***	(0.02)	0.37***	(0.03)	0.17***	(0.01)	0.27***	(0.02)	0.34***	(0.03)
Gender	–0.05***	(0.01)	–0.09***	(0.01)	–0.12***	(0.01)	–0.04***	(0.01)	–0.09***	(0.01)	–0.12***	(0.01)
Race	0.07***	(0.01)	–0.02**	(0.01)	0.15***	(0.03)	0.08***	(0.01)	–0.01	(0.01)	0.17***	(0.03)
Formality	–0.73***	(0.03)	0.60***	(0.05)	0.01	(0.06)	–0.80***	(0.03)	0.58***	(0.05)	–0.05	(0.06)
RTI	–0.19***	(0.03)	0.41***	(0.03)	0.27***	(0.04)	–0.11***	(0.03)	0.67***	(0.03)	0.59***	(0.04)
Specification error												
Education	–2.86***	(0.11)	–3.38***	(0.16)	–8.00***	(0.23)	–2.89***	(0.11)	–3.47***	(0.15)	–8.11***	(0.23)
Age	–0.18***	(0.04)	0.02	(0.05)	–0.39***	(0.10)	–0.19***	(0.04)	–0.02	(0.06)	–0.42***	(0.09)
Gender	–0.01	(0.03)	0.41***	(0.06)	0.45***	(0.08)	0.02	(0.03)	0.40***	(0.05)	0.50***	(0.08)
Race	–0.13***	(0.04)	–0.26***	(0.07)	0.15	(0.12)	–0.15***	(0.04)	–0.27***	(0.07)	0.08	(0.11)
Formality	–0.43***	(0.03)	–1.32***	(0.06)	–1.69***	(0.08)	–0.42***	(0.03)	–1.28***	(0.06)	–1.67***	(0.08)
RTI	–0.05	(0.03)	–0.23***	(0.06)	–0.65***	(0.08)	0.33***	(0.04)	0.28***	(0.06)	0.53***	(0.09)
Constant	2.52***	(0.12)	3.18***	(0.19)	5.28***	(0.26)	2.19***	(0.13)	2.77***	(0.18)	4.28***	(0.29)
Pure structure effects												
Education	0.06	(0.26)	1.05***	(0.38)	1.63***	(0.25)	–0.04	(0.25)	1.09***	(0.37)	1.43***	(0.26)
Age	0.59***	(0.16)	0.08	(0.26)	0.98***	(0.23)	0.57***	(0.16)	0.16	(0.25)	1.03***	(0.23)
Gender	–0.21	(0.16)	–0.48**	(0.23)	–0.75***	(0.24)	–0.12	(0.15)	–0.50**	(0.23)	–0.71***	(0.23)
Race	–1.10***	(0.16)	–0.13	(0.23)	–1.85***	(0.26)	–1.03***	(0.16)	–0.13	(0.23)	–1.75***	(0.26)
Formality	0.67***	(0.18)	0.20	(0.30)	0.70***	(0.27)	0.68***	(0.18)	–0.11	(0.29)	0.40	(0.26)
RTI	–0.17	(0.13)	0.17	(0.19)	0.28*	(0.16)	–1.44***	(0.12)	0.98***	(0.15)	–0.43**	(0.17)
Constant	–4.93***	(0.42)	–1.07**	(0.49)	–5.59***	(0.49)	–3.58***	(0.43)	–1.71***	(0.48)	–4.61***	(0.53)
Reweighting error												
Education	–0.01*	(0.00)	–0.04***	(0.00)	–0.10***	(0.01)	–0.01*	(0.00)	–0.04***	(0.00)	–0.09***	(0.01)
Age	–0.00**	(0.00)	–0.01***	(0.00)	–0.00	(0.00)	–0.00**	(0.00)	–0.01***	(0.00)	–0.00	(0.00)
Gender	0.00	(0.00)	–0.00***	(0.00)	–0.01***	(0.00)	0.00**	(0.00)	0.00***	(0.00)	–0.00	(0.00)
Race	–0.01***	(0.00)	–0.01***	(0.00)	–0.02**	(0.01)	–0.01***	(0.00)	–0.01***	(0.00)	–0.02**	(0.01)
Formality	–0.01*	(0.00)	–0.02***	(0.00)	–0.05***	(0.01)	–0.01*	(0.00)	0.01**	(0.00)	–0.03***	(0.01)
RTI	0.04***	(0.00)	0.02***	(0.00)	0.10***	(0.01)	0.02***	(0.00)	0.04***	(0.01)	0.07***	(0.01)
Observations	603,128		651,485		655,261		603,128		651,485		655,261	

Note: the years 2003, 2011, and 2018 also include data from 2004, 2012, and 2019, respectively. The table reports full results for RIF decompositions of the Gini, using reweighting. For details of the decomposition, see Equation 13. Bootstrap standard errors with 100 replications in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source: authors' compilation based on data from the PNAD (2003/04 and 2011/12) and PNADC (2018/19).

Table A3: RIF decomposition of Gini, reweighted approach (× 100), 2002/03–2011/12: FFM replication

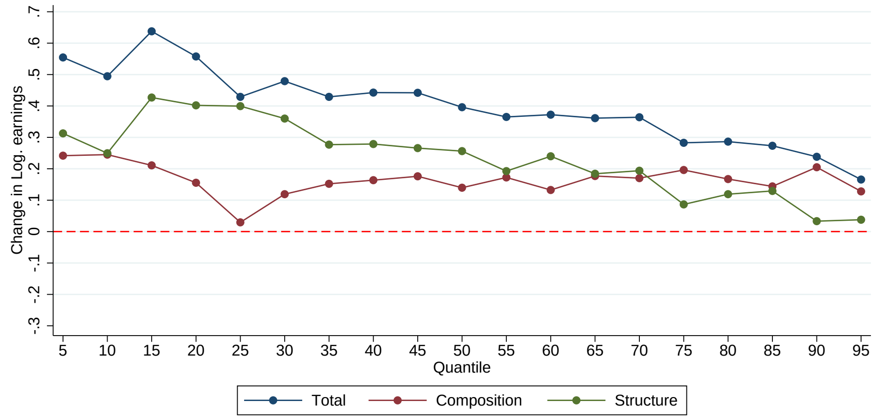
	No RTI		Country-specific RTI		O*NET RTI	
	(1)		(2)		(3)	
Gini, period 1	40.81***	(0.07)	40.81***	(0.07)	40.81***	(0.07)
Counterfactual	47.38***	(0.08)	47.21***	(0.08)	47.13***	(0.08)
Gini, period 2	46.60***	(0.07)	46.60***	(0.07)	46.60***	(0.07)
Gini, difference	–5.79***	(0.11)	–5.79***	(0.11)	–5.79***	(0.11)
Total composition	0.77***	(0.06)	0.61***	(0.06)	0.53***	(0.06)
Pure composition	1.68***	(0.07)	1.46***	(0.07)	1.37***	(0.07)
Specif. error	–0.91***	(0.03)	–0.85***	(0.02)	–0.85***	(0.02)
Total structure	–6.56***	(0.10)	–6.40***	(0.11)	–6.32***	(0.11)
Rwg. error	–0.16***	(0.01)	–0.21***	(0.01)	–0.21***	(0.01)
Pure structure	–6.40***	(0.10)	–6.19***	(0.10)	–6.11***	(0.10)
Pure composition effects						
Education	3.24***	(0.06)	2.61***	(0.06)	2.56***	(0.06)
Experience	–0.10***	(0.01)	–0.09***	(0.01)	–0.09***	(0.01)
Formality	–0.96***	(0.02)	–0.91***	(0.02)	–0.92***	(0.02)
Demography	–0.05***	(0.01)	–0.03***	(0.01)	–0.03**	(0.01)
Region	–0.08***	(0.01)	–0.09***	(0.01)	–0.09***	(0.01)
Sector	–0.36***	(0.02)	–0.16***	(0.02)	–0.27***	(0.02)
RTI			0.12***	(0.02)	0.22***	(0.02)
Specification error						
Education	–6.65***	(0.16)	–5.89***	(0.16)	–5.89***	(0.16)
Experience	–7.76***	(0.19)	–7.49***	(0.18)	–7.46***	(0.18)
Formality	–0.89***	(0.05)	–0.80***	(0.04)	–0.74***	(0.04)
Demography	0.10	(0.08)	0.09	(0.08)	0.06	(0.08)
Region	–0.94***	(0.11)	–0.86***	(0.11)	–0.89***	(0.11)
Sector	1.29***	(0.18)	0.85***	(0.16)	1.07***	(0.16)
RTI			0.47***	(0.06)	0.26***	(0.06)
Constant	13.95***	(0.35)	12.78***	(0.33)	12.73***	(0.34)
Pure structure effects						
Education	5.09***	(0.32)	4.62***	(0.32)	4.64***	(0.32)
Experience	5.26***	(0.43)	4.94***	(0.42)	4.99***	(0.42)
Formality	0.77***	(0.10)	0.66***	(0.10)	0.55***	(0.10)
Demography	–0.71***	(0.21)	–0.55***	(0.21)	–0.55***	(0.21)
Region	0.16	(0.25)	0.05	(0.26)	0.07	(0.26)
Sector	–1.16***	(0.45)	–0.67	(0.42)	–0.75*	(0.42)
RTI			–0.75***	(0.14)	–1.27***	(0.12)
Constant	–15.83***	(0.80)	–14.48***	(0.76)	–13.80***	(0.77)
Reweighting error						
Education	–0.15***	(0.01)	–0.12***	(0.01)	–0.12***	(0.01)
Experience	–0.02***	(0.00)	–0.02***	(0.00)	–0.02***	(0.00)
Formality	–0.01**	(0.00)	–0.02***	(0.00)	–0.02***	(0.00)
Demography	–0.01***	(0.00)	–0.01***	(0.00)	–0.01***	(0.00)
Region	–0.02***	(0.00)	–0.02***	(0.00)	–0.02***	(0.00)
Sector	0.05***	(0.00)	0.03***	(0.00)	0.04***	(0.00)
RTI			–0.05***	(0.01)	–0.06***	(0.01)
Observations	534,979		534,979		534,979	

Note: the table reports full results for RIF decompositions of the Gini, using reweighting. For details on the decomposition, see Equation 10. Bootstrap standard errors with 100 replications in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

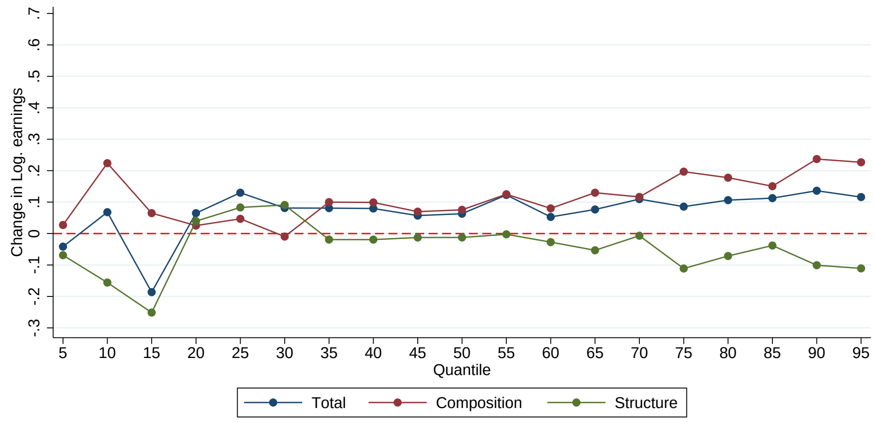
Source: authors' compilation based on data from the PNAD (2002/03 and 2011/12).

Figure A1: Aggregate decomposition by quantile, with reweighting

(a) 2003/04–2011/12



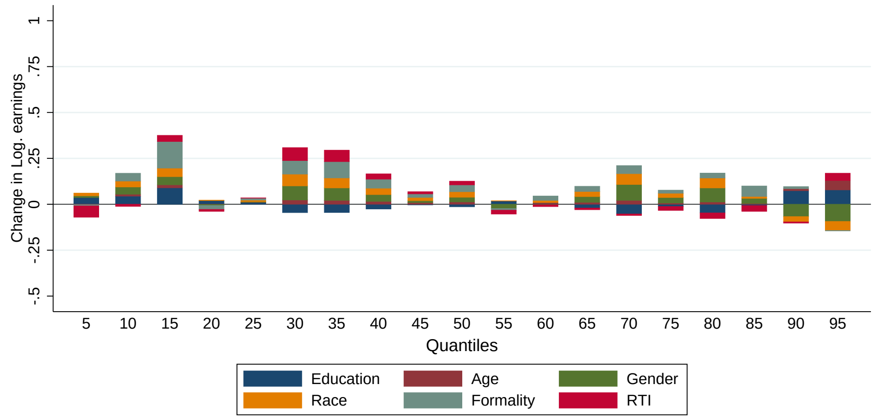
(b) 2011/12–2018/19



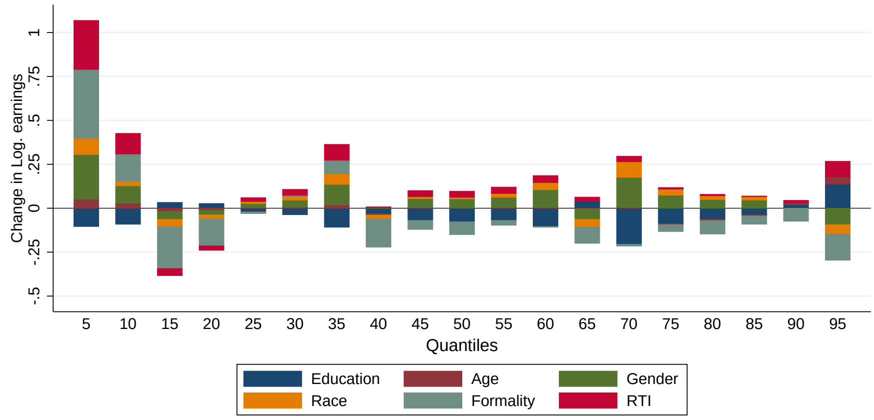
Note: these figures plot the changes in log earnings observed for the 5th to 95th quantiles, as well as the aggregated composition and structure effects estimated using RIF decompositions with reweighting (see Equation 13).

Source: authors' compilation based on data from the PNAD (2003/04 and 2011/12) and PNADC (2018/19).

Figure A2: Detailed decomposition by quantile, pure structural effects, with reweighting
(a) 2003–12



(b) 2012–19



Note: these figures plot the contribution of each factor to changes in log earnings observed for the 5th to 95th quantiles, based on the detailed decomposition of pure structural effects. The decomposition relies on RIF regressions with reweighting (see Equation 13).

Source: authors' compilation based on data from the PNAD (2003/04 and 2011/12) and PNADC (2018/19).

Appendix B: crosswalks: ISCO-CBO and COD-CBO

The Brazilian system of classification of occupations differs between the PNAD and PNADC. The one used by the PNAD is the Brazilian Classification of Occupations (*Classificação Brasileira de Ocupações*, CBO), while the PNADC employed the National Classification of Occupations for Household Surveys (*Classificação Nacional de Ocupações para Pesquisas Domiciliares*, COD). The 2010 Brazilian Census included both classifications in their survey. We use these data to create a crosswalk between the two classification systems. We group workers by their four-digit COD classification and the five-digit industry classification (CNAE 2.0) and assign to each pair the corresponding four-digit CBO occupation that is most common among them.

This method yields a perfect matching (that is, only one four-digit CBO occupation for each COD–industry pair) for more than 60 per cent of the pair, while the average share of the most common occupation within a pair is 89.7 per cent. Since this method relies on 439 COD–industry pairs, we do not replicate the crosswalk table here, but make it available upon request.

Once we matched the Brazilian classification systems, we match the CBO classification with the ISCO-88. The crosswalk is available in Table B1, and the corresponding codes are also available upon request

Table B1: Detailed Brazil-specific recodes

ISCO-88 (three digits)		CBO (three digits)	
Code	Label	Code	Label
111	Legislators and senior government	111	Advisers, secretaries, diplomats, and delegates
		112	Senior members of the legislative, executive, and judiciary
114	Senior officials of special-interest	114	Senior officers and administrators of public interest organization
121	Directors and chief executives	121	Support area directors
		122	Production and operations directors
		123	Managing directors
131	Managers of small enterprises	131	Administrators, advisers, assistants, heads and financial, administrative, operational, and commercial coordinators
		132	Directors and managers in a health, education, or cultural, social, or personal services company
211	Physicists, chemists, and related professionals	213	Physicists, chemists, and the like
212	Mathematicians, statisticians, and related professionals	211	Mathematicians, statisticians, and the like
213	Computing professionals	212	Computer professionals
214	Architects, engineers, and related professionals	201	Engineers, architects, and the like
		202	Biotechnology and metrology professionals
		214	Professionals in electromechanics
		215	Professionals in air, sea, and river navigation
221	Life science professionals	221	Agronomists and the like
		222	Biologists and the like
222	Health professionals (except nursing)	223	Medicine, health, and related professionals
231	College, university, and higher education teaching professionals	234	Higher education teachers
232	Secondary education teaching professionals	232	Secondary education teachers
233	Primary and pre-primary education teaching professionals	231	Vocational education teachers and instructors
235	Other teaching professionals	233	Other teaching professionals not previously classified
		239	Professional education teachers and instructors
241	Business professionals	252	Business organization and administration professionals and the like
242	Legal professionals	241	Judiciary and public security lawyers
		242	Lawyers, attorneys, notaries, and the like
244	Social science and related professionals	251	Social scientists, psychologists, and the like
245	Writers and creative or performing artists	253	Popular arts artists and models
		261	Technical designers and pattern makers
		262	Other mid-level technicians in the physical, chemical, engineering, and related sciences
		318	Communication and information professionals
		319	Entertainment and arts professionals
		376	Public relations, advertising, marketing, and marketing professionals
246	Religious professionals	263	Members of religious and related cults

ISCO-88 (three digits)		CBO (three digits)	
Code	Label	Code	Label
311	Physical and engineering science technicians	300	Physical and chemical science technicians
		311	Mid-level technicians in industrial operations
		312	Civil construction, building, and infrastructure technicians
		313	Electronics and photonics technicians
		314	Metal mechanic technicians
		316	Mineralogy and geology technicians
		391	Mechatronic and electromechanical technicians
312	Computer associate professionals	317	Computer technicians
313	Optical and electronic equipment operators	301	Laboratory technicians
		324	Technicians in the operation of sound, scenography, and projection equipment
		372	Camera, cinema, and television operation technicians
		373	Technicians operating radio stations, television systems, and video production companies
		374	Technicians operating diagnostic equipment and instruments
314	Ship and aircraft controllers and technicians	341	Air, sea, and river navigation technicians
		342	Transport technicians (logistics)
315	Safety and quality inspectors	352	Inspection and administrative coordination technicians
321	Life science technicians and related associate professional	320	Agricultural production technicians
		321	Biochemistry and biotechnology technicians
		325	Biology technicians
		328	Necropsy technicians and taxidermists
322	Health associate professionals (except nursing)	322	Animal health science technicians
		323	Human health science technicians
331	Primary education teaching associate professionals	331	Secondary-level teachers in kindergarten, elementary, and professional education
332	Pre-primary education teaching associate professionals	332	Lay teachers in primary and vocational education
334	Other teaching associate professionals	333	Student and related inspectors
		334	Free school instructors and teachers
341	Finance and sales associate professionals	354	Student and related inspectors
343	Administrative associate professionals	351	Administrative science technicians
		371	Cultural services technicians
347	Artistic, entertainment, and sports associate professionals	375	Athletes, sportspeople, and the like
		377	Decorators and window dressers
411	Secretaries and keyboard-operating clerks	412	Office secretaries and office machine operators
412	Numerical clerks	413	Accounting and finance clerks
413	Material-recording and transport clerks	414	Material control and production support clerks

ISCO-88 (three digits)		CBO (three digits)	
Code	Label	Code	Label
414	Library, mail, and related clerks	415	Library, documentation, and mail services assistants
419	Other office clerks	410	Dispatchers
		411	Interviewers, enumerators, and the like
		420	General clerks, agents, assistants, and administrative assistants
		423	Customer service supervisors
		424	Administrative services supervisors (except customer service)
421	Cashiers, tellers, and related clerks	421	Cashiers, box office, and the like
422	Client information clerks	422	Public information workers
511	Travel attendants and related workers	510	Service supervisors
		511	Hotel and catering services workers
		513	Transport and tourism service workers
513	Personal care and related workers	515	Healthcare workers
514	Other personal services workers	514	Product and accessories installers
		516	Workers in the services of administration, conservation, and maintenance of buildings and public places
		523	Workers in beautification and personal care services
516	Protective services workers	40	Cadet, warrant officer, sergeant, corporal, and soldier of the military police
		41	Cadet, warrant officer, sergeant, corporal and soldier of the military fire department
		50	Commander, lieutenant colonel, first and second lieutenant and military police captain
		51	Commander, lieutenant colonel, first and second lieutenant and captain of the military fire brigade
		517	Workers in protection and security services
522	Shop salespersons and demonstrators	520	Replenishers and trade markers
		521	Sales and service supervisors
		522	Vendors and demonstrators
611	Market gardeners and crop growers	612	Farmers
612	Animal producers and related workers	613	Livestock producers
613	Market-oriented crop and animal producers	611	Agricultural producers in general
711	Miners, shotfirers, stone cutters, and carvers	710	Mineral extraction and construction supervisors
		712	Mineral and ornamental stone processing workers
712	Building frame and related trades workers	715	Building helpers

ISCO-88 (three digits)		CBO (three digits)	
Code	Label	Code	Label
		716	Vehicle carpentry workers
		717	Construction and public works workers
		777	Construction finishing workers
713	Building finishers and related trades workers	724	Piping, steel, and composite assembly workers
714	Painters, building structure cleaners and related trades workers	716	Finishing construction workers
721	Metal moulders, welders, sheet-metal workers, structural-metal preparers, and related trades workers	720	Metal transformation and composites supervisors
		721	Metal and composite machining workers
722	Blacksmiths, tool-makers, and related trades workers	722	Metal and composites forming workers
		723	Metal and composites surface and heat treatment workers
723	Machinery mechanics and fitters	910	Maintenance mechanics of industrial, commercial, and residential machinery and equipment
		911	Maintenance mechanics of heavy machinery and agricultural equipment
		913	Vehicle maintenance mechanics
		914	Other conservation and maintenance workers (except elementary workers)
		991	Supervisors in repair and mechanical maintenance services
		992	Elementary maintenance workers
724	Electrical and electronic equipment mechanics and fitters	730	Industrial, commercial, and residential maintenance electronic electricians
		731	Vehicle maintenance electronic electricians
		732	Installers and repairers of electrical and communications lines and cables
		950	Electromechanical maintainers
		951	Assemblers and installers of electronic equipment in general
		953	Electroelectronic and electromechanical maintenance supervisors
		954	Supervisors of electronic assembly and installations
731	Precision workers in metal and related materials	740	Jewellers and goldsmiths
		741	Precision instrument assemblers and adjusters
		742	Musical instrument assemblers and fitters
		750	Precision instrument and equipment repairers
		751	Supervisors of precision mechanics and musical instruments
731	Precision workers in metal and related materials	915	Jewellery, glass, ceramic, and related supervisors
732	Potters, glassmakers, and related trades workers	752	Glassmakers, potters, and the like
733	Handicraft workers in wood, textile, leather, and related materials	760	Supervisors in the textile, tanning, clothing, and graphic arts industries
		761	Craftsmen of wood and furniture
		762	Craft workers in textile, clothing, and graphic arts activities
		768	Textile industry workers
		776	Leather and skincare workers
734	Craft printing and related trades workers	766	Graphic production workers
741	Food processing and related trades workers	848	Helper, assistant, cutter, cooker, dehydrator, and operator in the food industry

ISCO-88 (three digits)		CBO (three digits)	
Code	Label	Code	Label
		849	Craft workers in agribusiness, food, and tobacco industries
742	Wood treaters, cabinet-makers, and related trades workers	770	Joiners and the like
		771	Supervisors in the wood, furniture, and carpentry industry
		772	Wood preparation workers
		773	Woodworking and furniture manufacturing workers
		774	Workers assembling wooden furniture and artefacts
		775	Wood finishing and furniture workers
743	Textile, garment, and related trades work	763	Garment workers
744	Pelt, leather, and shoemaking trades workers	764	Fabric and leather artefact workers
		765	Footwear workers
815	Chemical processing plant controllers, operators	810	Plant operators in chemical, petrochemical, and related industries
		811	Production supervisors in chemical, petrochemical, and related industries
817	Industrial robot operators	781	Robot operators and special equipment
821	Metal- and mineral-products machine operators	820	Operators of metal and alloy production facilities and equipment—first merger
		821	Operators of installations and equipment for the production of metals and alloys—second fusion
		822	Production supervisors in steel industries
		823	Craft workers in the steel industry and construction materials
		828	Construction material, ceramic and glass plant and equipment workers
822	Chemical-products machine operators	812	Laboratory unit operation operators (cross-cutting to the entire process industry)
		813	Operators of other chemical, petrochemical, and related facilities
		818	Workers in the manufacture of ammunition and chemical explosives
825	Printing-, binding-, and paper-products machine operators	830	Paper and cardboard product manufacturers
		831	Pulp and paper manufacturing supervisors
		832	Papermaking workers
		833	Paper pulp preparation workers
827	Food and related products machine operators	840	Equipment operators in food and beverage preparation
		841	Operators in the preparation of tobacco and in the manufacture of cigars and cigarettes
		842	Food, beverage, and tobacco manufacturing supervisors
828	Assemblers	725	Production packers and feeders
		780	Assemblers of mechanical machines and apparatus
		784	Packaging and labelling worker supervisors

ISCO-88 (three digits)		CBO (three digits)	
Code	Label	Code	Label
829	Other machine operators and assemblers	860	Other plant operators
		861	Utility operators
		862	Operators in the generation and distribution of energy (hydro, thermoelectric, and nuclear power stations)
		871	Utilities production supervisors
831	Locomotive engine drivers and related workers	782	Vehicle drivers and lifting and handling equipment operators
911	Street vendors and related workers	524	Home, street, and newsstand vendors
913	Domestic and related helpers, cleaners, and launderers	512	General domestic service workers
914	Building caretakers, window and related cleaners	991	Facade cleaners and conservation aides
915	Messengers, porters, doorkeepers, and related workers	519	Other miscellaneous service workers
921	Agricultural, fishery, and related labourers	620	Supervisors in agricultural exploration
		621	Fishermen and hunters
		622	Supervisors in agricultural exploration
		623	Forestry and Fishing supervisors
		630	Agricultural workers
		631	Irrigation and drainage workers
		632	Agricultural mechanization workers
		641	Forest mechanization workers
		642	Workers in agricultural exploration in general
		643	Livestock workers
931	Mining and construction labourers	711	Mineral extraction workers
933	Transport labourers and freight handlers	783	Rail shunting and cargo handling workers

Source: authors' compilation.