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Examining the Drivers of Changes in Mean Earning and Earning Inequality in Indonesia

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Abstract

This paper examines the main drivers behind changes in mean earning and earning inequality in Indonesia between 2001/2 and 2018. During this period, there was an increase in workers' education level, average age, job quality, and mean earnings. As more women participate in the labor market and women earn lower wages than men, higher female labor force participation lowered mean earning. For the overall period, the decline in educational returns at all levels of education contributed negatively to earnings. Gini index increased during this period, driven by education distribution effect and spatial location premium effect. Albeit educational improvement increased mean earning, it was inequality-increasing due to the "paradox of progress". The narrowing wage premia across districts contributed to the increase in mean earning. There is a the need for complementary policies to attenuate the inequality-increasing education and spatial location effects as well as gender wage gap.

JEL Classification: J31, J38

Keywords: Inequality, Labor Market

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Examining the Drivers of Changes in Mean Earning and Earning Inequality in Indonesia

Maria Monica Wihardja and Abror Tegar Pradana[1]

1. Introduction

Cross-country studies show that labor income is the key, if not the most important, contributor to poverty reduction in many countries (see, for example Azevedo et al. (2013)). Moreover, good quality job is a key pathway to middle-class. Indonesia is no exception. Although poverty rate has reached a single digit for the first time in Indonesia's history in 2018, the large majority of Indonesians who live in vulnerability (one in five Indonesians) and who aspire but lack the economic security to join the middle class (one in two Indonesians)[2] mean that Indonesia still faces a huge challenge in increasing the majority of Indonesians' standard of living and welfare – mainly through better quality jobs. In addition to this, during the commodity boom era followed by a premature deindustrialization where employment in the medium and large manufacturing firms was 'hollowed out', inequality skyrocketed from 30 points in 2000 to 37.8 points in 2010. The Gini coefficient continued to rise to 41.4 points in 2014, its highest recorded level. The increase in consumption inequality has been partly driven by earning inequality (Wihardja & Cunningham, 2021).

This paper is seeks to investigate the main drivers behind changes in mean earning and earning inequality in Indonesia as mean earning and earning inequality will determine the pace of poverty reduction and expansion of its middle-class as well as quality of its economic growth. Low earning and high earning inequality will also potentially threaten Indonesia's political stability. Studying the drivers behind changes in mean earning and earning inequality will help

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[1] This paper is part of the background paper for the World Bank Indonesia Jobs Report, Pathways to Middle Class Jobs in Indonesia. All views expressed in this paper are of the authors and do not represent the views of the affiliations with which the authors are or have been affiliated.

[2] Poor are defined as those who live below the poverty line. Vulnerable are defined as those who have more than 10 percent probability of going into poverty (whose monthly household consumption is around 1-1.5 times the poverty line). Aspiring Middle Class are defined as those who have more than 10 percent probability of going into poverty and vulnerability (whose monthly household consumption is around 1.5-3.5 times the poverty line). Middle Class are defined as those who have less than 10 percent probability of going into poverty and vulnerability (whose monthly household consumption is around 3.5-17 times the poverty line). Upper Class are defined as those whose consumption is above 17 times the poverty line (World Bank, 2019).

policy makers identify and focus on necessary reforms to increase earnings and reduce earning inequality in Indonesia.

Following the work done in Ferreira et al. (2022), we decompose changes in mean earning and earning inequality into distribution (or endowment) and structure (or premium) effects that each consists of explanatory variables based on individual worker's characteristics, namely education, age, job status, gender, location, economic sector of employment, and occupation.[3]

A wide body of literature has shown that contributors to changes in mean earning and earning inequality in each country vary. Ferreira et al. (2022) show that increase in the mean earning in Brazil is associated with changes in sectoral employment premium. On the other hand, earning inequality has been driven primarily by education distribution effect. The inequality-increasing distribution of education effect is also found in India by Khanna et al. (2016). However, in this case, the inequality-increasing distribution education effect is offset by the decrease of return to education in the upper quintiles.

Some of the literature in this area of research also finds that minimum wage plays a role in changes of earning inequality in developing countries. Ferreira et al. (2022) find that contribution of minimum wage to increasing earning inequality in Brazil has been associated with labor market condition, in which labor market is not able to afford the increase in minimum wage and increasing non-compliance by employers to pay worker at or above the minimum wage. Due to data limitation and high non-compliance of firms paying workers at or above the minimum wage in Indonesia, we exclude minimum wage as an explanatory variable.

Moreover, Chi et al. (2011) find that premium effects, such as gender, earning differentials between industries, company ownership type, and regions are the major contributors to the increased earning inequality in China. Biewen & Seckler (2019) exhibit different results in Germany, in which the composition effects have the most substantial role in explaining earning inequality, especially the part coming from de-unionization.

This paper contributes to the existing body of literature by applying the Fortin et al. (2011)'s re-centered influence function (RIF) methodology, also employed in Ferreira et al. (2022), using Indonesia's Labor Force Survey data, to decompose changes in mean earning and earning inequality in Indonesia in the period of 2001/2-2011 (the commodity boom era), 2011-

[3] We use the word 'distribution effect' and 'endowment effect' interchangeably, and 'structure effect' and 'premium effect' interchangeably.

2018 and 2001/2-2018. As far as to our knowledge, there has not been any decomposition analysis on mean earning and earning inequality using RIF methodology using Indonesia's Labor Force Survey data. Findings from this paper should help policy-makers navigate, reflect and prioritize policies related to creation of better-quality jobs that is inclusive for all. In particular, findings from this paper shed some lights on policies related to education, gender gap and equal distribution to accrued benefits.

The next section will explain to the readers the data and methodology that are used in this paper. The section following the next will discuss the main results. The paper will conclude with a summary of the findings, limitations of the findings and policy recommendation.

2. Data and Methodology

2.1 Data

This paper relies on Indonesia Labor Force Survey (*Survei Tenaga Kerja*-Sakernas) as primary data source, which is published by the Statistics Indonesia-BPS. The Sakernas is collected by BPS twice a year, February and August. This dataset is representative at the level of province in February and district in August. For the purpose of this study and considering the number of sample size (50,000 households in February and 200,000 household in August), we build a pooled dataset from 2001, 2002, August 2011, and August 2018 data. We combine Sakernas 2001 and 2002 as one period since Sakernas 2001 and 2002 has relatively smaller number of observations (Sakernas 2001 has 104,978 observations and 2002 has 191,857 observations while 2011 has 524,810 observations and 2018 has 508,562 observations).

The dataset contains information at the individual level. The respondents are all workers aged 15 years old and above. However, earnings information is only available for individuals who work as self-employed, employees, and casual workers but not employers (who earns business profits) and unpaid family workers (with implicit earnings). Interpretation of the findings should take this limitation into account. We also exclude individuals who reported negative earnings during the survey period. Earnings are converted into real value using CPI deflator and 2018 as the base year. Indonesia has also experienced district proliferation since 1998, thus we trace proliferated districts back to their parent districts in 1993. After trimming the 1^{st} and 99^{th} percentiles on earnings due to potential outliers, our sample size consists of 99,000 workers in 2001/2002, 180,000 workers in 2011 and 200,000 workers in 2018.

As explanatory variables, we use individual characteristics, namely education, age, job status, gender, whether individuals live in urban or rural, economic sector of employment, occupation, and province where individuals live. All variables are categorical, except earnings, education age. Regarding the change in classification in employment sector and occupation, we categorize workers to 9 employment sectors and 8 occupational categories. Job status is often considered as formality status, in which BPS classifies employees as formal workers and self-employed and casual workers as informal workers. Educational attainment is defined as the highest educational level completed, converted into years of education[4].

2.2 Methodology

In this study, we compare earnings in the two periods – 'pre' that shows the first observed period and 'post' that shows the last observed period. Blinder (1973) explains there are two sources that contribute to earning differentials, which are changes in characteristics distribution and changes in conditional distribution on workers' characteristics. The characteristics distribution is usually called as 'endowment' and refers to the distribution of the labor market. The conditional distribution is usually called as 'structure' and refers to the return or premium of workers' characteristics. The most common method to decompose contributions of distribution vis-à-vis premium is by using the decomposition method developed by Blinder (1973) and Oaxaca (1973). In this study, we are interested in comparing earnings between two periods, suppose t_1 and t_0. Using linear regression, we have relationship between wage and individual characteristics as follows

(1) $y_i = \beta_0 + \sum_{j=1}^{n} \beta_j X_{ji} + u_i$

where y_i is the individual i's earnings in natural logarithm, and $X_{1i}, \dots, X_{ni}$ are n observed characteristics of individual i. For each period, we have

(2) $y_{1,i} = \beta_{1,0} + \sum_{j=1}^{n} \beta_{1,j} X_{1,ji} + u_{1,i}$

(3) $y_{0,i} = \beta_{0,0} + \sum_{j=1}^{n} \beta_{0,j} X_{0,ji} + u_{0,i}$

Also, we have a model for earnings that pool the two-period observations:

(4) $y_i = \beta_0 + \sum_{j=1}^{n} \beta_j X_{ji} + u_i$

[4] We convert the school level as follows: no schooling or not completed elementary school is 0, elementary school is 6, junior high school is 9, senior high school is 12, diploma I/II is 14, diploma III is 15, and undergraduate or higher is 16.

Assume the unobservable components are not correlated with observable ones, earnings differentials can be explained by:

(5) $\bar{y}_{1,i} - \bar{y}_{0,i} = \sum_j \hat{\beta}_j\left(\bar{X}_{1,j} - \bar{X}_{0,j}\right) + \sum_j[\bar{X}_{1,j}(\hat{\beta}_{1,j} - \hat{\beta}_j) + \bar{X}_{0,j}(\hat{\beta}_j - \hat{\beta}_{0,j})] + (\hat{\beta}_{1,0} - \hat{\beta}_{0,0})$

The first sum of equation (5) is the estimated distribution effects that determine how changes in average earnings can be explained by the changes in characteristics distribution, $\hat{\Delta}_X^{\mu} = \hat{\beta}_j\left(\bar{X}_{1,j} - \bar{X}_{0,j}\right)$, while the second term is the estimated premium effects that estimate how changes in average earnings can be explained by the changes in premiums, $\hat{\Delta}_S^{\mu} = \bar{X}_{1,j}\left(\hat{\beta}_{1,j} - \hat{\beta}_j\right) + \bar{X}_{0,j}\left(\hat{\beta}_j - \hat{\beta}_{0,j}\right)$. The last term, $\left(\hat{\beta}_{1,0} - \hat{\beta}_{0,0}\right)$ is considered as unobservable factors that explain the differentials.

We are interested to examine not only the average earnings differentials, but also the inequality measures as well as the growth incidence. Fortin et al. (2011) extend the Oaxaca-Blinder decomposition to decompose other features of distribution. Their approach is using re-centered influence function (RIF) regression. In this approach, RIF regression is similar to the standard regression except we replace the dependent variable with the re-centered influence function. To summarize their approach (see Firpo et al. (2009) for details), suppose q_τ is the τ-th quantile of dependent variable, y, with the distribution F_y. Then the influence function, $IF\left(y; q_\tau, F_y\right)$ is equal to $(\tau - \mathbb{1}\{Y \leq q_\tau\})/f_Y(q_\tau)$. Then, the re-centered influence function is defined as $RIF\left(y; q_\tau, F_y\right) = q_\tau + IF\left(y; q_\tau, F_y\right)$. Furthermore, the conditional expectation of $RIF(y; v)$ of explanatory variable X, $\mathrm{E}\left[RIF\left(y; q_\tau, F_y\right)\middle|X\right] = X\gamma$ can be estimated using OLS where γ is the vector of parameters.

Our study replicates Ferreira et al. (2022) that utilizes mean μ, Gini coefficient G, and the τ^{th} percentile q_t as outcomes of interest. Essama-Nssah & Lambert (2012) provide the list of the formula to construct the indicators in term of influence function. Let v be a functional of earnings distribution. Thus, we have

(6) $\hat{\Delta}_X^{v} = \sum_{j=1}^{n} \hat{\beta}_j^{v}(\bar{X}_{1,j} - \bar{X}_{0,j})$

(7) $\hat{\Delta}_S^{\mu} = \sum_{j=1}^{n} \bar{X}_{1,j}(\hat{\beta}_{1,j}^{v} - \hat{\beta}_j^{v}) + \bar{X}_{0,j}(\hat{\beta}_j^{v} - \hat{\beta}_{0,j}^{v})$

where $\hat{\beta}_{t,j}^{v}$ are the coefficients of variables j in a regression of re-centered influence function of v on X for period t.

We categorize the contribution of variables, both distribution and premium effects, to eight groups of individual characteristic attributions, which are educational attainment, age, job status, gender, location, economic sector, and occupation. Since the RIF decomposition is the extension of Oaxaca-Blinder (OB) decomposition, then there is no difference compared to the common OB decomposition. We can quantify the contribution of distribution and premium effects to the change in the distribution of Y.

Since most our variables are categorical, then we drop the most advantaged group as the control group since the more disadvantaged groups are more likely to have higher wage growths than the most advantaged group and dropping the most advantaged group can minimize the effects of unobserved components in the decomposition Ferreira et al. (2022).

3. Results

3.1 Changes in Labor Market Distribution

One source of changes in the mean earning and earning inequality is changes in the distribution of workers by workers' characteristics, such as education, potential work experience (proxied by age), occupation, economic sector of employment, employment status, location, and gender. Table 1 displays that Indonesia has experienced a significant increase in the years of education of paid workers (wage employees, self-employed and casual workers), from 7.7 years in 2001 to 9.3 years in 2018. The average age of workers increased slightly from 36.4 to 38.9, indicating a slightly older workforce with more work experience.

Other characteristics disaggregated by gender and residency show that the share of female workers out of total workers increased by around four percentage points and workers who lived in rural areas declined by six percentage points within the same time period.

In terms of job status, the share of wage employees increased by six percentage points to 58 percent in 2018, while the share of self-employed decreased by around seven percentage points to 28 percent and the share of casual workers hovered at around 14 percent. Workers were more likely to move out from the agriculture, forestry, livestock and fishing sector; the manufacturing sector; the transportation, storage and communications sector *into* the construction sector; wholesale and retail trade, restaurants and hotels; finance, insurance, real estate, and business sector; and community, social and personal services. This is analogous to the tertiarization of the economy during the period. In terms of occupational employment, the shares of sales and services workers as well as skilled farmers (i.e. middle-skilled jobs) in the workforce declined while the shares of professional, technical, and related workers and administrative and managerial workers (i.e. high-skilled jobs) and the shares of production and related workers, transport equipment operators, and laborers as well as other blue-collar workers (i.e. low-skilled jobs) increased, indicating the hollowing-out of middle-skilled jobs. Real monthly wage goes up by around 50 percent in the last 17 years.

Table 1. Descriptive Statistics

Variables	Mean		
	2001/2002	2011	2018
years of education	7.65	8.46	9.26
Age	36.36	36.98	38.85
status: self-employment	0.35	0.27	0.28
status: employee	0.52	0.56	0.58
status: casual worker	0.14	0.16	0.14
Female	0.31	0.32	0.35
Rural	0.44	0.40	0.38
sector: agriculture, forestry, livestock and fishing	0.21	0.19	0.17
sector: mining and quarrying	0.01	0.02	0.01
sector: manufacturing	0.18	0.16	0.17
sector: electricity, gas, and water supply	0.00	0.00	0.01
sector: construction	0.07	0.09	0.09
sector: wholesale and retail trade, restaurants and hotels	0.21	0.20	0.22
sector: transportation, storage and communications	0.08	0.07	0.07
sector: finance, insurance, real estate, and business	0.02	0.04	0.04
sector: community, social and personal services	0.20	0.23	0.21
occupation: professional, technical, and related workers	0.06	0.10	0.10
occupation: administrative and managerial workers	0.00	0.01	0.01
occupation: clerical and related workers	0.08	0.08	0.09
occupation: sales workers	0.19	0.17	0.16
occupation: services workers	0.08	0.08	0.07
occupation: agriculture, animal husbandry, forestry workers, fishermen, and hunters	0.21	0.18	0.16
occupation: production and related workers, transport equipment operators, and laborers	0.37	0.37	0.39
occupation: others	0.01	0.01	0.03
real monthly wage (IDR)	1,495,194.00	1,653,099.00	2,244,065.00
log(real monthly wage)	13.97	14.03	14.34

Source: Authors' calculation with data from LFS 2001, 2002, 2011, and 2018

3.2 Changes in Labor Market Premiums

Another source of changes in mean earning and earning inequality is changes in the wage premia across different workers' characteristics. We utilize the Mincerian equation to estimate the partial relationships between explanatory variables of interest and mean earning (taking the best performing segment of workers for each variable of interest as the control group). Table 2 reports the coefficients from an OLS regression of real monthly wages in natural logarithm by year.

Figure 1 shows that the convex-shaped return to education decreased between 2001/2002 and 2018 for almost all levels of education. In contrary, age (as a proxy to potential work experience) vs. earning profile as shown in Figure 2 shows that the concave-shaped return to age increased between 2001/2002 and 2018 for all age levels. Table 2 shows that there was an increasing wage gap between self-employed workers and wage employees, but a declining wage gap between casual workers and wage employees. Gender wage gap narrowed slightly, where female workers earned 37 percent lower in 2001/2002 and 36 percent lower in 2018 compared to male workers. This narrowing gender wage gap could reduce the overall earning inequality while the increasing share of female workforce in the labor market narrows the gender labor force participation gap. Rural-urban wage gap widened between 2001/2 and 2018. Working in the rural areas, holding everything else constant, a worker earned 6.8 percent lower than its urban counterpart in 2001/2002, but 12.5 percent lower in 2018.

Sectoral employment's premia show that except for mining and quarrying (2011, 2018), manufacturing (2018), utilities (2001/2002), and construction (2001/2002, 2011, 2018), all other sectoral employment earns relatively less than those in finance and other business sector (the highest-paying sector) *controlling* for other variables.[5] In terms of occupational employment, the wage gap between administrative and managerial jobs (the highest paying occupation) and other occupational employment declined, except for professional, technical and related workers. Other unobserved factors, lumped into a constant, have remained quite unchanged.

To better understand how changes in the education premium and age premium might affect mean earning and earning inequality, we plot the education-earning and age-earning profiles across different periods of time (Figure 1 and Figure 2). The education-earning profile shows convexity

[5] Although the construction sector has positive coefficients for the three years, unconditional of other variables, the mean wage in the construction sector is less than that of the finance and other business sector. The finance and other business sector has the highest mean wage compared to other sectors in all three years.

of return to education (so called "the paradox of progress"), while the age-earning profile shows concavity of return to age (diminishing return of age on earning). This education-earning and age-earning profiles are consistent with what is found in the Brazilian case (Ferreira et al., 2022).

Table 2. Labor Market Premium

VARIABLES	(1) 2001/2002	(2) 2011	(3) 2018
years of education	0.0209***	0.0310***	0.0182***
	(0.00321)	(0.00290)	(0.00300)
(years of education^2)/100	0.0863	-0.282***	-0.0556
	(0.0544)	(0.0487)	(0.0481)
(years of education^3)/1000	0.0529**	0.294***	0.158***
	(0.0245)	(0.0215)	(0.0205)
Age	0.0474***	0.0491***	0.0476***
	(0.000981)	(0.000820)	(0.000842)
(age^2)/100	-0.0511***	-0.0510***	-0.0504***
	(0.00123)	(0.000997)	(0.000995)
status: self-employment	-0.0717***	-0.0472***	-0.230***
	(0.00615)	(0.00535)	(0.00560)
status: casual worker	-0.288***	-0.230***	-0.272***
	(0.00748)	(0.00617)	(0.00645)
Female	-0.368***	-0.310***	-0.359***
	(0.00519)	(0.00457)	(0.00470)
Rural	-0.0680***	-0.0560***	-0.125***
	(0.00514)	(0.00436)	(0.00429)
sector: agriculture, forestry, livestock and fishing	-0.0698**	-0.0222	-0.0241
	(0.0319)	(0.0232)	(0.0187)
sector: mining and quarrying	0.00129	0.224***	0.203***
	(0.0252)	(0.0169)	(0.0170)
sector: manufacturing	-0.0290*	0.0138	0.0369***
	(0.0163)	(0.0125)	(0.0110)
sector: electricity, gas, and water supply	0.113***	0.0169	-0.0521**
	(0.0374)	(0.0352)	(0.0233)
sector: construction	0.0830***	0.159***	0.167***
	(0.0173)	(0.0132)	(0.0118)
sector: wholesale and retail trade, restaurants and hotels	-0.0391**	-0.0391***	-0.0265**
	(0.0173)	(0.0131)	(0.0109)
sector: transportation, storage and communications	-0.00167	-0.0632***	0.00476
	(0.0175)	(0.0135)	(0.0118)

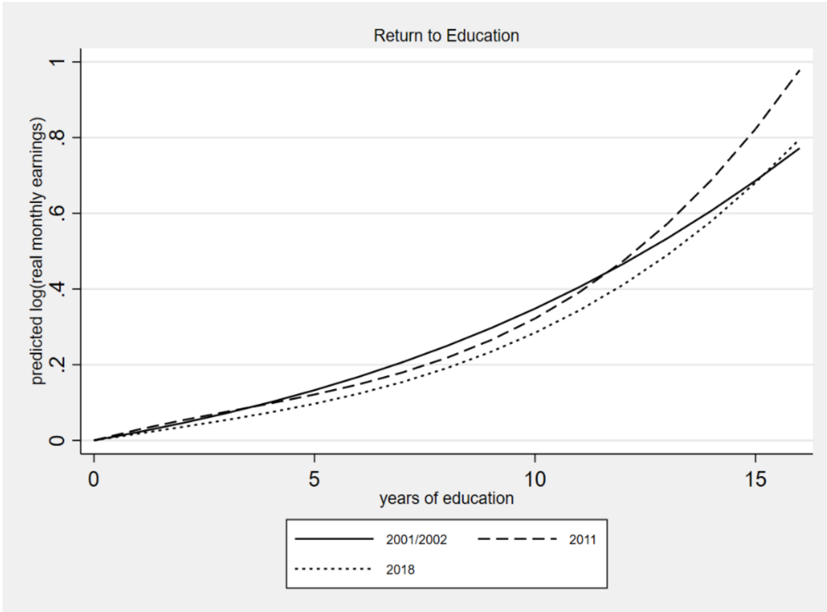
Table 2. Labor Market Premium (Cont'd)

sector: community, social and personal services	-0.103***	-0.212***	-0.273***
	(0.0161)	(0.0120)	(0.0106)
occupation: professional, technical, and related workers	-0.108***	-0.274***	-0.278***
	(0.0406)	(0.0208)	(0.0179)
occupation: clerical and related workers	-0.160***	-0.0931***	-0.109***
	(0.0399)	(0.0208)	(0.0172)
occupation: sales workers	-0.347***	-0.374***	-0.223***
	(0.0407)	(0.0222)	(0.0183)
occupation: services workers	-0.518***	-0.450***	-0.352***
	(0.0406)	(0.0214)	(0.0184)
occupation: agriculture, animal husbandry, forestry workers, fishermen, and hunt	-0.613***	-0.578***	-0.486***
	(0.0489)	(0.0291)	(0.0237)
occupation: production and related workers, transport equipment operators, and laborers	-0.373***	-0.414***	-0.337***
	(0.0400)	(0.0207)	(0.0171)
occupation: others	0.181***	0.497***	-0.0897***
	(0.0431)	(0.0259)	(0.0202)
Constant	13.88***	13.48***	13.94***
	(0.0500)	(0.0305)	(0.0277)
	99513	186593	201706
Observations	1244.8	1509.5	1376.4
R-squared	0.438	0.354	0.333
Province FE	Yes	Yes	Yes

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

Source: Authors' calculation with data from Sakernas 2001, 2002, 2011, and 2018

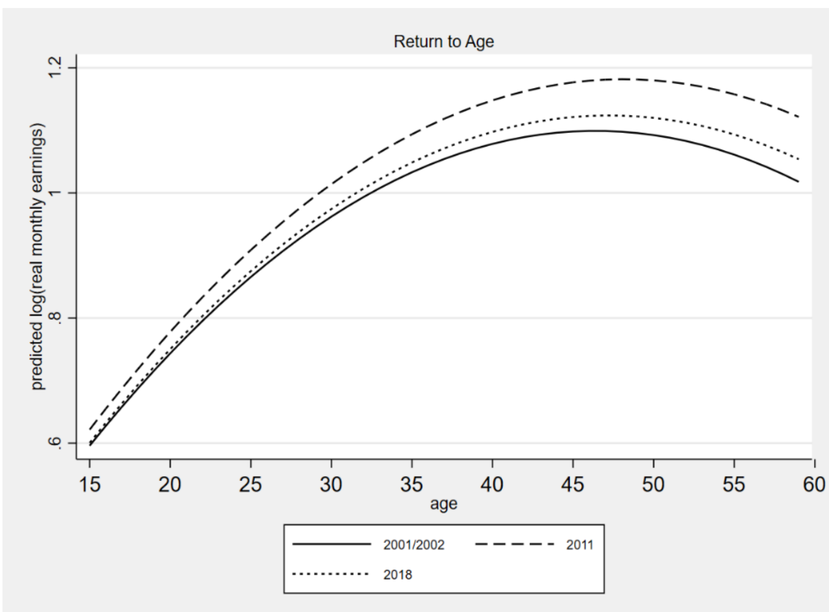
Figure 1. Return to Education



Note: Predicted values using coefficients from Table 2.

Source: Authors' calculation using Sakernas 2001, 2002, 2011 and 2018

Figure 2. Return to Age



Note: Predicted values using coefficients from Table 2.

Source: Authors' calculation using Sakernas 2001, 2002, 2011 and 2018

3.3 Results from the Decomposition of Mean Earning

Table 3 reports the Blinder-Oaxaca decomposition of differences in average earnings in the whole period 2001/2-2018 and two sub-periods 2001/2-2011 and 2011-2018. The year 2011 is chosen as the mid-period as it marks the end of the commodity boom era that started in 2001. We group the explanatory variables of interest into seven: education, age (a proxy to potential work experience), job status, gender, location, economic sector, and occupation.

The overall log earning increased from 13.97 to 14.34 between 2001/2 and 2018. Almost two thirds of this increase were accounted for by changes in the premium or returns of the explanatory variables, while changes in the distribution of the explanatory variables contributed to the rest of the one third. About 85 percent of the average earning increase in this period was explained by the increase that happened during the second half of the period, i.e. 2011-2018. This may indirectly imply that during Indonesia's high-growth, commodity boom period in 2001-2011, economic growth did not trickle down to a substantial increase in earnings of paid workers.

The decomposition of the premium and distribution effects is as follows. As expected, the distribution of education throughout the whole period and the two sub-periods was contributing positively to mean earning as Indonesians became more educated with higher earnings (see Table 1 and Table 2). The distribution effect from location was also positive to mean earning for the whole period and the first sub-period 2001/2-2011, partly contributed by workers moving to urban areas with higher earnings on average compared to rural areas. The positive distribution effect from location may also mean that workers moved from provinces with lower earnings to provinces with higher earnings on average. Similarly, for job status, as there were more wage employees relative to self-employed with lower earnings that wage employees on average, job status was also contributing positively to earnings for the whole period and the second sub-period 2011-2018, although the effect was relatively small compared to the other abovementioned variables. As workers moved out of the low-wage agricultural sector (see Table 1), earnings also increased on average for the whole period and the two sub-periods because of workers moving from the low-earning agricultural sector to other higher-earning sectors. And as the share of workers with high-skilled jobs (professionals, technicians, administrative, and managerial, etc.) increased, occupational employment was also contributing positively to mean earning for the whole period and the two sub-periods.

The only variable with a negative distribution effect was gender. Since more women were participating in the labor force and women earn less than men on average (see Table 1 and Table 2), the distribution effect of gender brought mean earning for the whole period and for the two sub-periods, although this effect was relatively small.

Table 3. Mean Decomposition

	Overall		
	2018 - 2001/2002	2011 - 2001/2002	2018 - 2011
Post	14.34159***	14.0277***	14.34159***
	[0.00166]	[0.00156]	[0.00231]
Pre	13.97171***	13.97171***	14.0277***
	[0.00376]	[0.00394]	[0.00201]
Difference	0.36988***	0.05598***	0.3139***
	[0.00411]	[0.00424]	[0.00306]
Endowments	0.14197***	0.08542***	0.06785***
	[0.00204]	[0.00194]	[0.00156]
Structure	0.22791***	-0.02943***	0.24605***
	[0.00381]	[0.00383]	[0.00276]

	Endowments		
	2018 - 2001/2002	2011 - 2001/2002	2018 - 2011
Education	0.082***	0.04474***	0.04517***
	[0.00116]	[0.00098]	[0.00088]
Age	0.01583***	0.00688***	0.01016***
	[0.00061]	[0.00053]	[0.00049]
Job Status	0.0082***	-0.00239***	0.00536***
	[0.00048]	[0.00045]	[0.00034]
Gender	-0.01342***	-0.00343***	-0.00894***
	[0.00068]	[0.00063]	[0.00052]
Region and Urban/Rural	0.02214***	0.02283***	0.00013
	[0.00067]	[0.0007]	[0.00052]
Economic Sector	0.00387***	0.00044	0.00442***
	[0.00077]	[0.00055]	[0.00051]
Occupation	0.02336***	0.01636***	0.01154***
	[0.00101]	[0.00086]	[0.00054]

Table 3. Mean Decomposition (Cont'd)

	Structure		
	2018 - 2001/2002	2011 - 2001/2002	2018 - 2011
Education	-0.03647***	0.00636	-0.05074***
	[0.01031]	[0.01044]	[0.00762]
Age	0.01669	0.06264*	-0.04716**
	[0.03225]	[0.03329]	[0.02313]
Job Status	-0.04546***	0.01658***	-0.05681***
	[0.00446]	[0.00466]	[0.00291]
Gender	0.00344	0.01839***	-0.01599***
	[0.00293]	[0.00296]	[0.00219]
Region and Urban/Rural	0.17177***	0.28269***	-0.11174***
	[0.02504]	[0.02619]	[0.01329]
Economic Sector	-0.00382	-0.00227	-0.00254
	[0.02716]	[0.02875]	[0.0148]
Occupation	0.0596	-0.01308	0.06813***
	[0.06647]	[0.07032]	[0.02588]
Constant	0.06216	-0.40074***	0.4629***
	[0.0843]	[0.08879]	[0.04087]

Notes: Robust standard errors in brackets. Significant level *** p<0.01, ** p<0.05, * p<0.1. Each category is the sum of individuals effects. Education and age refer to years of education and its polynomial degree and age and its polynomial degree, respectively. Job status consists of two dummies: self-employment and casual worker. Gender refers to dummy variables that takes value one for female. Region and Urban/Rural summarize the contribution dummy rural and province fixed effects. Economic sector includes eight employment sectors (finance, insurance real estate, and business as base category) while occupation captures seven dummy variables of occupation (administrative and managerial workers as base category).

Source: Authors' calculation with data from Sakernas 2001, 2002, 2011, and 2018

The declining return to education at almost all levels of education and changes in the returns to employment status, especially the higher wage penalty from being self-employed relative to wage employees, lowered mean earning (Table 3). But, these negative premium effects were largely offset by a positive premium effect of location (urban-rural and district effects). Since the wage penalty from living in rural areas was lower relative to urban areas, the positive premium effect of location was likely to come from the province effect, i.e. a lower wage penalty from living in lower-paying province relative to higher-paying province. Changes in earning premia across age, gender and occupational employment contributed positively to mean earnings although the premium effects of these variables were insignificant.

Breaking changes in mean earning down to the two sub-periods, the increasing return of age between 2001/2 and 2011 at all levels of age contributed positively to mean earning for this period while the decreasing return of age in the subsequent sub-period at all levels of age contributed negatively to mean earning for this period. The narrowing wage gap between female and male between 2001/2 and 2011 contributed positively to mean earning in this sub-period while the widening wage gap between female and male between 2011 and 2018 contributed negatively to mean earning in this subsequent period. The net premium effect of gender between 2001/2 and 2018 was positive but insignificant. The narrowing gap between most of occupational employment and managerial occupation (highest-paying occupation) between 2011 and 2018 contributed positively and significantly to mean earning during that sub-period.

3.4 Decomposition – Gini Index

Between 2001/2 and 2018, Indonesia saw an increase of its Gini index by 1.95 percentage points from 37.07 to 39.01, as shown in Table 4. This number hides the striking difference in how the Gini moved between the two sub-periods: 3.5 percentage point increase between 2001/2 and 2011 and 1.53 percentage point *decline* between 2011 and 2018. The rise of the Gini between 2001/2 and 2011 coincided with the commodity boom era (heavy reliance on exports of natural resources, primarily coal and palm oil) that led to a premature deindustrialization (low growth of the manufacturing sector) and tertiarization of the economy (high growth of the service sectors).

Table 4. Gini Decomposition

	Overall		
	2018 - 2001/2002	2011 - 2001/2002	2018 - 2011
Post	39.013***	40.538***	39.013***
	[0.054]	[0.048]	[0.082]
Pre	37.067***	37.067***	40.538***
	[0.13]	[0.137]	[0.068]
Difference	1.945***	3.471***	-1.525***
	[0.141]	[0.145]	[0.106]
Endowments	1.066***	0.68***	0.588***
	[0.054]	[0.042]	[0.037]
Structure	0.88***	2.79***	-2.113***
	[0.146]	[0.145]	[0.104]

Table 4. Gini Decomposition (Cont'd)

	Endowments		
	2018 - 2001/2002	2011 - 2001/2002	2018 - 2011
Education	0.912***	0.378***	0.456***
	[0.04]	[0.024]	[0.021]
Age	0.182***	-0.028***	0.216***
	[0.011]	[0.01]	[0.01]
Job Status	-0.155***	0.092***	-0.109***
	[0.014]	[0.013]	[0.007]
Gender	0.266***	0.066***	0.154***
	[0.014]	[0.012]	[0.009]
Region and Urban/Rural	-0.188***	-0.169***	-0.031***
	[0.015]	[0.014]	[0.008]
Economic Sector	-0.017	0.107***	-0.149***
	[0.031]	[0.024]	[0.017]
Occupation	0.065*	0.234***	0.051***
	[0.038]	[0.031]	[0.018]
	Structure		
	2018 - 2001/2002	2011 - 2001/2002	2018 - 2011
Education	-0.313	0.527	-0.762***
	[0.404]	[0.411]	[0.287]
Age	-0.071	1.45***	-1.527***
	[0.461]	[0.477]	[0.325]
Job Status	1.025***	-0.32*	1.208***
	[0.159]	[0.167]	[0.1]
Gender	-0.425***	-0.962***	0.583***
	[0.105]	[0.105]	[0.082]
Region and Urban/Rural	16.669***	12.617***	4.064***
	[1.62]	[1.702]	[0.578]
Economic Sector	3.019**	1.272	1.772**
	[1.474]	[1.56]	[0.812]
Occupation	8.708*	1.529	6.958***
	[4.559]	[4.81]	[1.811]
Constant	-27.733***	-13.323**	-14.41***
	[5.043]	[5.317]	[2.126]

Notes: Robust standard errors in brackets. Significant level *** p<0.01, ** p<0.05, * p<0.1. Each category is the sum of individuals effects. Education and age refer to years of education and its polynomial degree and age and its polynomial degree, respectively. Job status consists of two dummies: self-employment and casual worker. Gender refers to dummy variables that takes value one for female. Region and Urban/Rural summarize the contribution dummy rural and province fixed effects. Economic sector includes eight employment sectors (finance, insurance real estate, and business as base category) while occupation captures seven dummy variables of occupation (administrative and managerial workers as base category).

Source: Authors' calculation with data from Sakernas 2001, 2002, 2011, and 2018

For the overall period, the increase in the Gini was contributed by both the inequality-increasing distribution and premium effects. The increase in the Gini between 2001/2 and 2011 was contributed mainly by the inequality-increasing premium effect, while the decline in the Gini between 2011 and 2018 was mostly contributed by the inequality-reducing premium effect. For both sub-periods, the distribution effect was inequality-increasing.

The largest contributor to the inequality-increasing distribution effect between 2001/2 and 2018 was education, contributing 0.91 percentage point increase. Education distribution effect, albeit increasing mean earning, was increasing earning inequality because of what is known as the "paradox of progress" (Bourguignon et al., 2005; Ferreira et al., 2022). This paradox argues that the marked convexity of the earning-education profile at the higher level of education (see Figure 1) increases inequality as the level of education improves since a larger mass of workers moves to the part of the earning-education profile where schooling premia are higher or highest. Education distribution effect was inequality-increasing for both sub-periods, but larger in the latter sub-period.

The other contributors to the inequality-increasing distribution effect were gender and age, although their contributions were smaller than education. Gender distribution effect was inequality-reducing for both periods, but the effect in the latter sub-period was double that of the early sub-period. The inequality-increasing gender distribution effect was perhaps the result of more women participating in the labor market, mostly in the low service sectors with low wages, but when they work in the high service sectors, they earn higher than men (Wihardja & Cunningham, 2021). Hence, female workers potentially have a higher wage dispersion relative to male workers, potentially increasing earning inequality (see Table 6 for the statistics).

Table 5. Mean Real Monthly Earnings by Category

	Mean Real Earnings (IDR)		
	2001/2002	2011	2018
Education			
Primary education, or lower	1,080,124	1,123,509	1,546,418
Lower secondary education	1,458,752	1,528,042	1,903,620
Upper secondary education	1,957,567	1,903,774	2,515,732
Diploma I/II/III	2,760,157	2,735,094	3,211,106
University/Diploma IV, or greater	2,961,869	3,371,662	3,760,506
Location			
Rural	1,258,730	1,374,533	1,751,521
Urban	1,683,906	1,841,667	2,548,609
Job Status			
Self-employed	1,342,366	1,429,259	1,808,480
Employee	1,767,528	1,949,821	2,637,129
Casual worker	863,811	1,010,358	1,481,441
Economic Sector			
Agriculture, forestry, livestock and fishery	1,000,337	1,131,177	1,422,566
Mining and quarrying	1,634,509	2,278,900	2,901,536
Manufacturing	1,421,698	1,517,395	2,315,780
Electricity, gas, and water supply	2,488,440	2,428,615	2,590,512
Construction	1,494,033	1,584,056	2,234,356
Wholesale and retail trade, restaurants	1,416,062	1,518,376	2,123,148
Transportation, storage and communication	1,666,714	1,662,504	2,499,523
Finance, insurance, real estate and business	2,391,431	2,488,464	3,377,932
Community, social and personal services	1,995,463	2,138,843	2,599,922
Occupation			
Professional, technical, and related worker	2,633,025	2,691,738	3,138,195
Administrative and managerial workers	3,492,187	3,688,704	4,379,602
Clerical and related workers	2,451,055	2,548,764	3,275,248
Sales workers	1,388,033	1,479,750	2,135,710
Services workers	1,214,060	1,411,697	1,739,630
Agriculture, animal husbandry, forestry workers, fishermen, and hunters	984,988	1,102,959	1,384,143
Production and related workers, transport equipment operators, and laborers	1,445,891	1,468,179	2,141,084
Others	3,150,193	4,071,737	3,304,072

Source: Authors' calculation with data from Sakernas 2001, 2002, 2011, and 2018

The inequality-increasing distribution effects coming from education, gender and age were attenuated by the inequality-reducing distribution effects coming from job status and spatial locations. However, these inequality-reducing distribution effects were much smaller in magnitude than the inequality-increasing distribution effects. The location distribution effect was inequality-reducing for both sub-periods, but it became less inequality-reducing in the latter sub-period. Meanwhile, job status distribution effect changed from inequality-increasing in the early sub-period to inequality-decreasing in the latter sub-period.

Table 6. Mean Log(real monthly wage) by Gender and Sector

Sector	Male	Female
Agriculture, forestry, livestock and fishery	13.83544	13.24346
	(0.7151817)	(0.686044)
Mining and quarrying	14.3917	13.78182
	(0.7838864)	(0.8857202)
Manufacturing	14.31602	13.84601
	(0.6279375)	(0.7721043)
Electricity, gas, and water supply	14.55452	14.25277
	(0.6860851)	(0.938524)
Construction	14.25066	14.2438
	(0.5640349)	(0.6923959)
Wholesale and retail trade, restaurants	14.27785	13.9017
	(0.6358356)	(0.7101075)
Transportation, storage and communication	14.25538	14.38491
	(0.6507942)	(0.8058566)
Finance, insurance, real estate and business	14.64428	14.64461
	(0.6903742)	(0.7667991)
Community, social and personal services	14.45173	14.05669
	(0.8116015)	(0.9559378)

Note: Standard deviations are in parentheses.

Source: Sakernas 2001, 2002, August 2011, August 2018

Moving from the distribution effect to the premium effect on changes in earning inequality, the inequality-reducing premium effect in the 2011-2018 sub-period was offset by the inequality-increasing premium effect in the 2001/2-2011 sub-period, resulting in an inequality-increasing premium effect of the overall period. The main drivers of the inequality-increasing premium effect for the overall period came from the increasing conditional gaps associated with location, job status, economic sectors, and occupation. The increasing wage penalty from working in location or types of jobs that were already (most) disadvantaged to begin with (relative to other location or jobs) seems to contribute to earning inequality. Although we did not look at the impact of minimum wages in this decomposition analysis, minimum wages may contribute to wage penalty in terms of location. For example, one of the reasons why people migrate to Jakarta is the expected higher salary induced by the high minimum wage relative to other regions in Indonesia.

On the other hand, the equalizing structure of returns to unobserved skills, captured by the inequality-reducing constant term (Ferreira et al., 2022), has largely attenuated the inequality-increasing premium effects coming from location, job status, economic sectors, and occupation. The constant term was inequality-reducing in both sub-periods. The slightly falling conditional gender earnings gap between 2001/2 and 2018 has also offset the inequality-increasing premium effects.

3.5 Growth Incidence Curves

Using the RIF-regression decompositions for each quantile of the earnings distribution, we plot the overall decomposition of observed log income differences at each percentile into distribution and premium effects. Panel A, Figure 3-5, show the Growth Incidence Curves (GIC) and the decomposition of GIC into distribution and premium effects for the overall period 2001/2-2018 and its sub-periods (2001/2-2011, 2011-2018). For the overall period, the total and the distribution effects are upward-sloping along most of the GIC (indicating an inequality-increasing effect). Meanwhile, the premium effect is mildly upward sloping in the middle distribution before increasing more significantly in the upper percentile. This result is consistent with the earlier result on the decomposition of the Gini index, which shows that an increase in Gini in this period was contributed by both the distribution and premium effects.

The GIC for the sub-periods are also largely consistent with the result on the decomposition of the Gini index. In the 2001/2-2011 sub-period, both the distribution and premium effects as well as the total effect show strong upward-sloping GIC, resulting in a significant increase in the Gini.

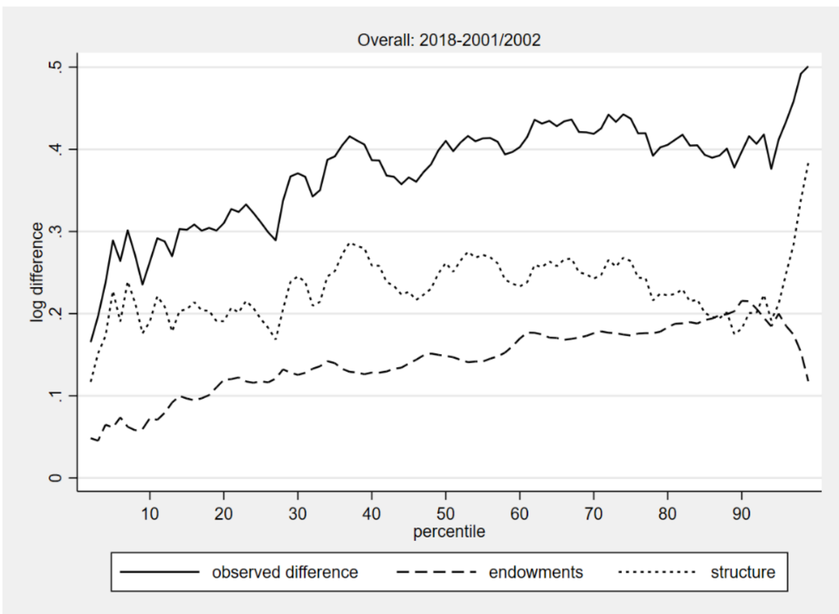
In the meantime, in the 2011-2018 sub-period, the graphs are largely reversed. The premium effect graph is an inverted-U shaped with a strong downward-sloping curve at right tail, in line with the result on the decomposition of the Gini index that shows an inequality-reducing premium effect. Meanwhile, the distribution effect is upward-sloping, in line with the result on the decomposition of the Gini index that shows an inequality-increasing distribution effect. Overall, the combination between premium and distribution effects results in an inverted-U shaped curve, in line with the inequality-reducing total effect for the period of 2011-2018 as shown in the decomposition of the Gini index.

Looking at the GIC of the earnings changes at each percentile into detailed distribution and premium effects shows a strong upward-sloping premium effect of region and urban/rural and a milder upward sloping distribution effect of education. These are again consistent with the result on the decomposition of the Gini Index that shows that these two components mainly drove the inequality-increasing total effects. Meanwhile, the GIC of the constant term in the structure component shows a strong downward-sloping curve, in line with the result on the decomposition of the Gini Index, which shows a large inequality-reducing constant term reflecting the equalizing structure of returns to unobserved skills.

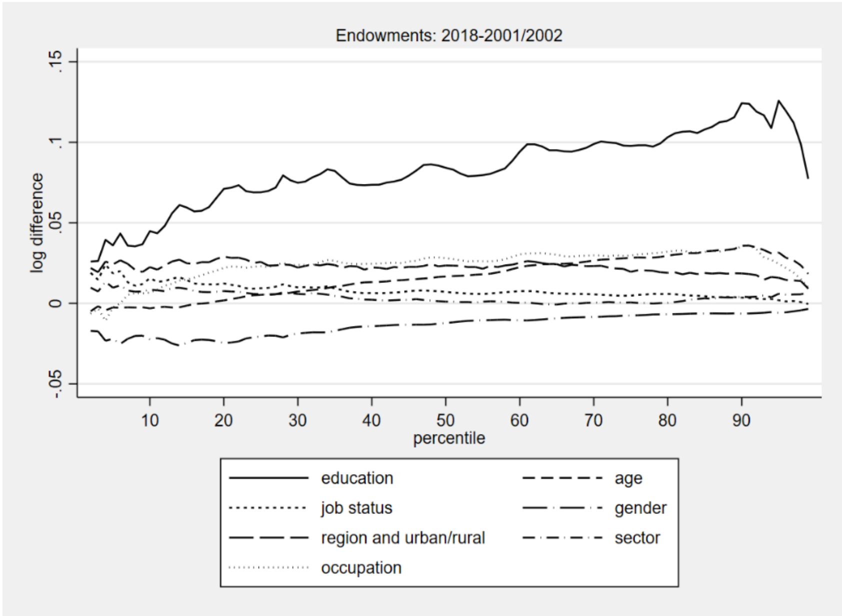
The GIC could also explain why, for example, the location distribution effect was inequality-reducing in both sub-periods (downward-sloping GIC) and job status distribution effect changed from inequality-increasing in the early sub-period (upward-sloping GIC) to inequality-decreasing (downward-sloping GIC) in the latter sub-period.

Figure 3. GIC Decomposition 2018-2001/2002

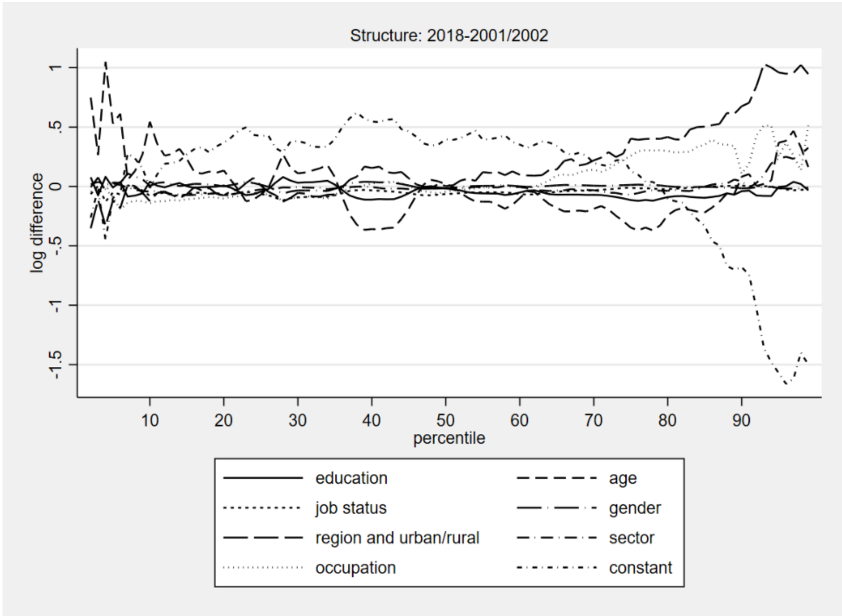
Panel A



Panel B



Panel C



Panel D

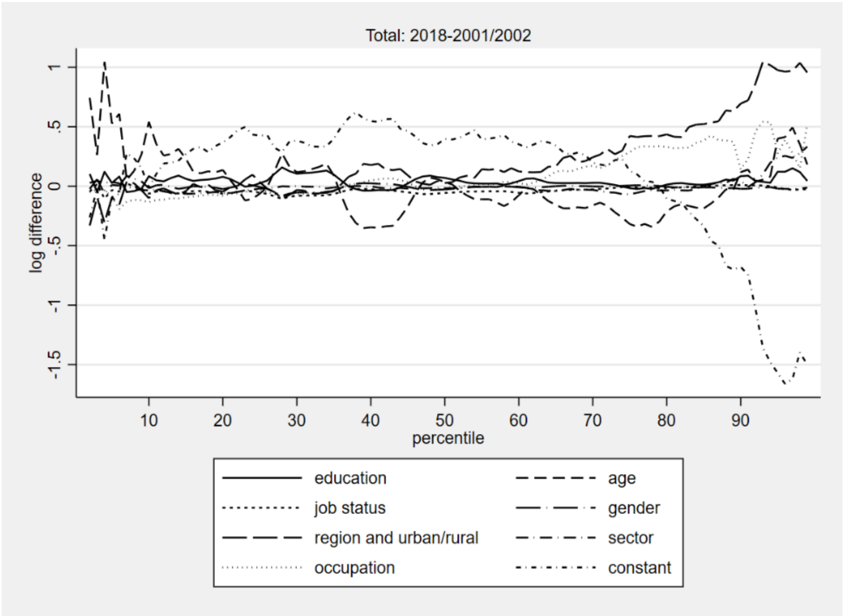
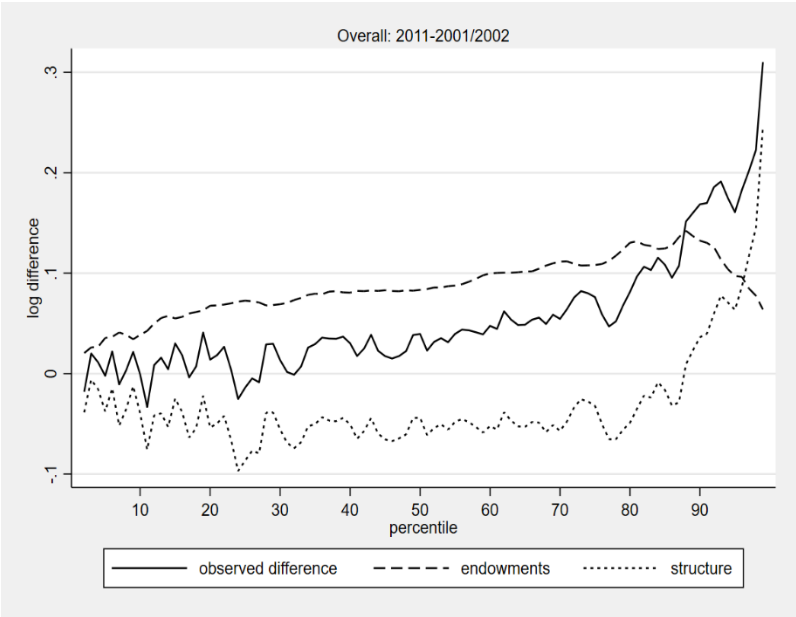
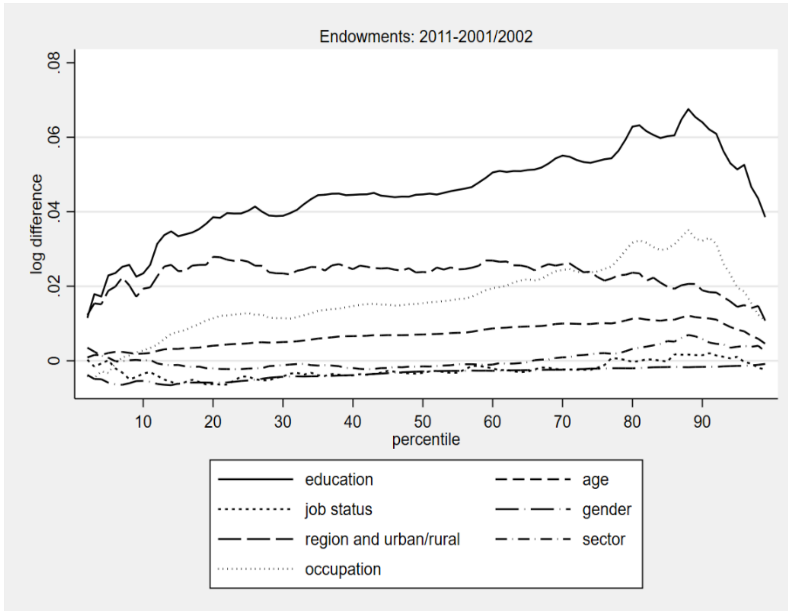


Figure 4. GIC Decomposition 2011-2001/2002

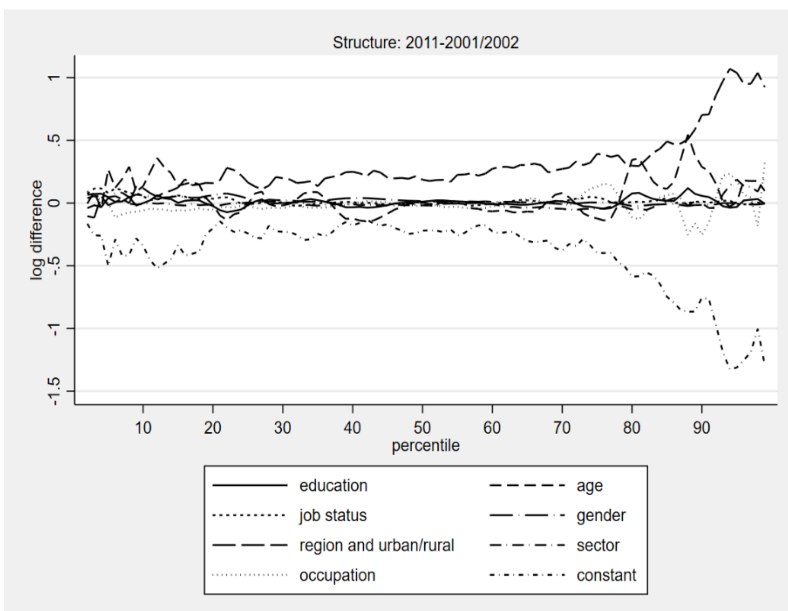
Panel A



Panel B



Panel C



Panel D

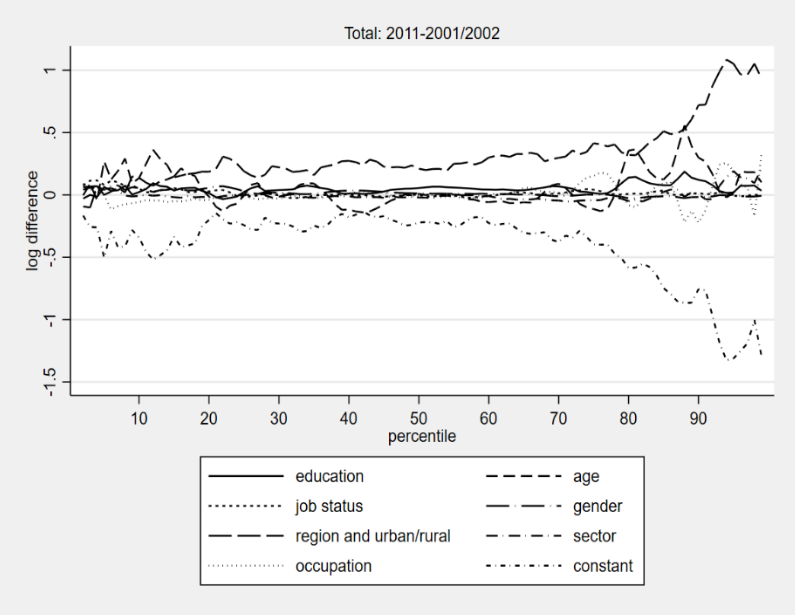
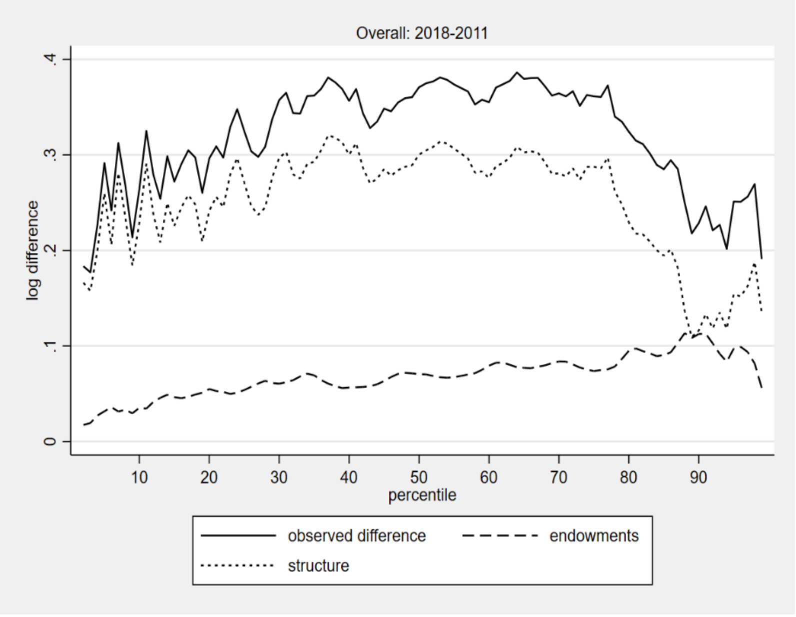
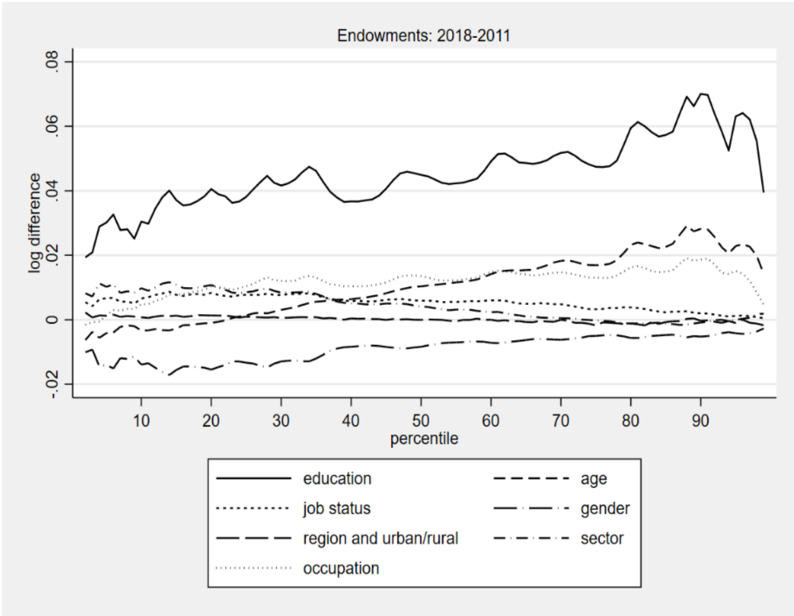


Figure 5. GIC Decomposition 2018-2011

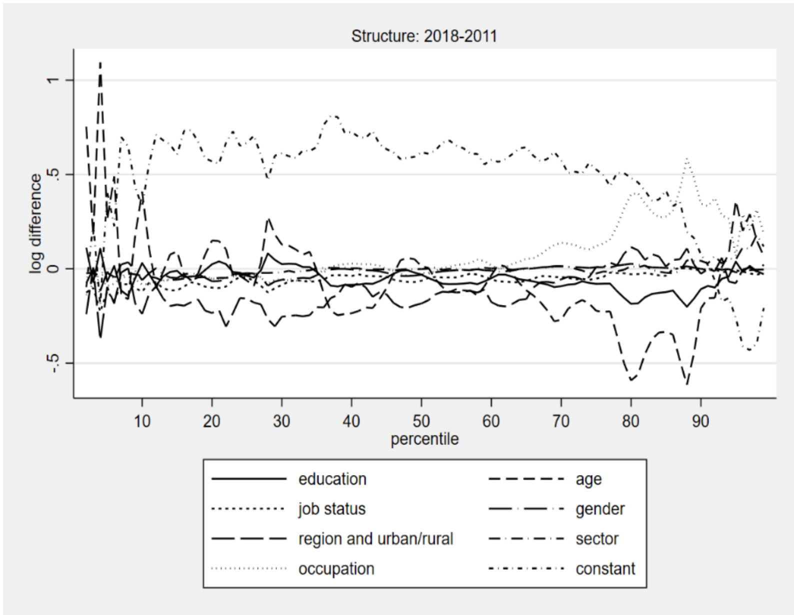
Panel A



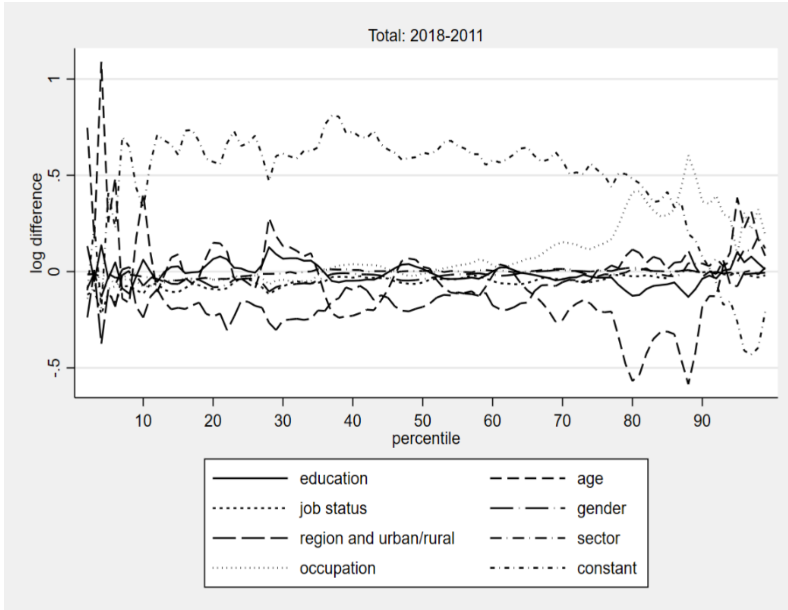
Panel B



Panel C



Panel D



4. Conclusion

Although poverty rate has reached a single digit for the first time in Indonesia's history in 2018, the large majority of Indonesians who live in vulnerability (one in five Indonesians) and who aspire but lack the economic security to join the middle class (one in two Indonesians) indicate that Indonesia still faces a huge challenge in increasing the majority of Indonesians' standard of living and welfare – mainly has to go through better quality jobs. Between 2000 and 2014, coincidently when Indonesia had one of its highest growth periods, Indonesia's Gini skyrocketed from 30 points to 41.4 point in 2014, the fastest increase in inequality ever seen in East Asia and Pacific region. World Bank (2016) attributed this rising Gini to a widening wage gap due to increasing skill/education premium, among others. This implies that the increase in consumption inequality has been partly driven by earning inequality.

In this paper, we ask the question: what have been the main drivers behind changes in mean earning and earning inequality in Indonesia. Following the work done in Ferreira et al. (2022), we decompose changes in mean earning and earning inequality into distribution and premium effects that each consists of explanatory variables based on individual worker's characteristics, namely age, gender, education, location, job status, economic sector of employment, and occupation.

We find that the overall log earning increased from 13.97 to 14.34 between 2001/2 and 2018. The difference was accounted for by changes in both the distribution and premium effects. About 85 percent of the average earning increase in this period was explained by the increase that happened during the second half of the period, i.e. 2011-2018, which implies that during Indonesia's high growth period in 2001/2-2011, economic growth did not trickle down to a substantial increase in mean earning of paid workers. The positive distribution effects coming from education, age, job status, spatial location, economic sector, and occupation were marginally offset by the negative distribution effect coming from gender. As workers' educational level improved, average age increased (but still remains in the productive age range), job quality improved in terms of job status, occupation and economic sector, mean earning also improved. However, as more and more women participated in the labor market and women earned lower wages than men, this gender-driven demographic shift lowered mean earning.

For the overall period, the decline in educational return at almost all levels of education contributed negatively to mean earning. The higher penalty (widening wage gap) by being self-employed relative to being wage employees contributed to the negative premium effect of job status to mean earning. These negative premium effects were largely offset by a larger positive premium effect coming from spatial location, in particular the district effect instead of the rural-urban effect. This could mean a lower wage penalty from living in lower-paying districts relative to higher-paying districts.

The decomposition result for the earning inequality shows that the increase in the Gini between 2001/2 and 2018 was contributed by both the inequality-increasing distribution and premium effects. While the first sub-period contributed to the rising Gini index, the second sub-period partly offset this contribution. The increase in the Gini between 2001/2 and 2011 was contributed mostly by the premium effect, while the decline in the Gini between 2011 and 2018 was also contributed mostly by the premium effect.

The largest contributor to the inequality-increasing distribution effect between 2001 and 2018 was education. Education distribution effect, albeit increasing the mean earning, was increasing inequality because of what is known as the "paradox of progress" (Bourguignon et al., 2005; Ferreira et al., 2022). The inequality-increasing distribution effects coming from education, but also age, gender and occupation, were attenuated by the inequality-reducing distribution effects coming from job status and spatial location. Meanwhile, the biggest contributor to the inequality-increasing premium effect on the increase in Gini for the whole period 2001-2018 came from the spatial location, while the biggest contributor to the inequality-reducing premium effect came from the constant term reflecting the equalizing structure of returns to unobserved skills.

The results from the RIF quantile regressions were largely consistent with the results on the decomposition of the Gini index and could help explain changes in the Gini index that might not be so well-explained from the decomposition analysis.

There are some limitations to this paper and methodology used in this paper. First, the RIF decomposition does not establish a causality relationship. Second, the Sakernas data only provides earning data for paid workers namely employees, casual workers and self-employed. Third, interpretations of the RIF quantile regression must be made in a global sense. Hence, results from the RIF quantile regression are often difficult or not possible to be interpreted at the quantile level.

Some policy implications from the findings in this paper highlight the need for complementary policies to attenuate the inequality-increasing education effects although mean earning increases as educational level of workers increases. Moreover, declining gender wage gap has been shown to reduce earning inequality. Progressive policies to narrow gender wage gap is therefore critical. The fact that changes in the distribution of and returns on location (urban-rural and district effects) increased mean earning but also earning inequality highlights the importance to ensure an inequality-reducing instead of an inequality-increasing distribution of the narrowing wage gap across regions in Indonesia.

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