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Inequality and structural transformation in the changing nature of work

The case of Indonesia

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Abstract: This paper analyses the labour market dynamics in Indonesia from 2001 to 2015 and explores the role of the changing nature of occupational employment in explaining the rising earnings inequality during the same period. First, we find evidence of a disproportionate increase in the returns to tertiary education, the increasing shares of highly skilled and elementary workers, and a sign of job polarization. Second, we find evidence of job polarization in the periods 2005–10 and 2005–15. Third, using reference influence function regressions, we quantify the extent to which changes in inequality over time can be attributed to changes in the distributions of worker characteristics and changes in the returns to these characteristics. The results suggest that in all the periods where Gini of earning is rising, the changing earnings structure, most notably returns to education, residency, and possibly routine-task intensity, contributes to the rise.

Key words: labour market dynamics, inequality, occupational employment, earnings inequality

JEL classification: J21, J24, D63

Note: Technical Appendix available here (https://www.wider.unu.edu/publication/inequality-and-structural-transformation-changing-nature-work)

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1 Introduction

Structural transformation or the transition of an economy from lower- to higher-productivity activities has been the key to achieving higher economic growth. For Indonesia, a country that aspires to become a high-income economy before its 100 years' anniversary of independence (1945–2045), that high and sustained economic growth, higher than what the country has experienced for the last two decades, is the key. For a country that experienced quite successful industrialization during the 1980s and 1990s, the new structural transformation that can enable it to jump-start the stalled industrialization in the last two decades can be seen as the only solution.

Economic growth is not Indonesia's only problem. Despite its success in lowering poverty incidence, the country's population is still economically vulnerable. Data from the World Bank World Development Indicator suggests that 53 per cent of the Indonesian population (in 2018) is either in extreme and moderate poverty or economically vulnerable (see World Bank 2020). In contrast, Malaysia, its closest neighbour, has an insecure population (i.e. those who live below 2018 PPP $5.5 per person per day) of only 3.7 per cent. The other neighbouring country, Thailand, has an economically vulnerable population of 8.4 per cent.

The vulnerability and insecurity of the economy has proven to be a serious problem during the COVID-19 pandemic. In September 2020, the worst months of the COVID-19 pandemic, Indonesian poverty incidence (by national poverty line) increased to the level it was 3 years ago (BPS 2021). This is despite the massive amount of social assistance given to the poor and vulnerable population (Sparrow et al. 2020).

One may argue (Yusuf et al. 2014; Yusuf and Sumner 2015) that the high vulnerability of the Indonesian population despite moderate economic growth is because the economic growth is not considered inclusive. The period from 2000 to 2012 was one of unprecedented rising inequality. This was also the period in which structural transformation had a different character compared with the period before the Asian financial crisis (AFC) of 1997–98. The period before the AFC was one of rather inclusive growth, where economic growth stood consistently at around 7 per cent with poverty declining and inequality remaining stable. This was a period of rapid industrialization. However, during the 2000s, industrialization stalled and agriculture continued to shrink in terms of both value added and employment. What happened was more and more tertiarization of employment. The tertiary sectors holding all of these incoming new workers are sectors that are not modern, have low productivity, and are often informal.

The link between structural transformation and inequality has been continuously at the centre of debates in development economics since Kuznets (1955, 1973). In the context of rising inequality in Indonesia, which happened quite remarkably during a short period of time, the structural transformation explanation of this is more appealing than other hypotheses. Some other factors such as commodity boom and fiscal policies have been discussed. Yet, commodity boom is often temporary and government size (in terms of fiscal policies and its power to affect income distribution) in the Indonesian economy is still low. Therefore, structural transformation during the period of rising inequality in Indonesia helps to better understand the nature and cause of the rising inequality.

One may argue that structural transformation and inequality are both outcomes of some other process (endogenous variables). So, eventually it will be difficult to determine the direction of causation between the two. To explain the cause of inequality, economists naturally look for some more exogenous factors such as technological changes. Technological changes can affect both structural transformation and inequality.

To find the cause of rising inequality in advanced economies during the 1980s and 1990s, economists turned to the skill-biased technical change hypothesis (Johnson 1997; Berman et al. 1998; Card and DiNardo 2002). Highly skilled workers benefited more from new information and communication technology (ICT), and this new technology displaced low-skilled jobs. The new ICTs increased returns from skills (Katz and Autor 1999).

An alternative hypothesis, routine-biased technical change (RBTC), referring to a shift away from manual and routine cognitive work towards non-routine cognitive work was put forward by economists (Autor et al. 2003; Acemoglu and Autor 2011; Goos and Manning 2007; Goos et al. 2014; Harrigan et al. 2016). In the context of advanced economies, RBTC vis-à-vis labour market polarization has been sufficiently established. RBTC can explain the rising inequality, at least, in advanced economies.

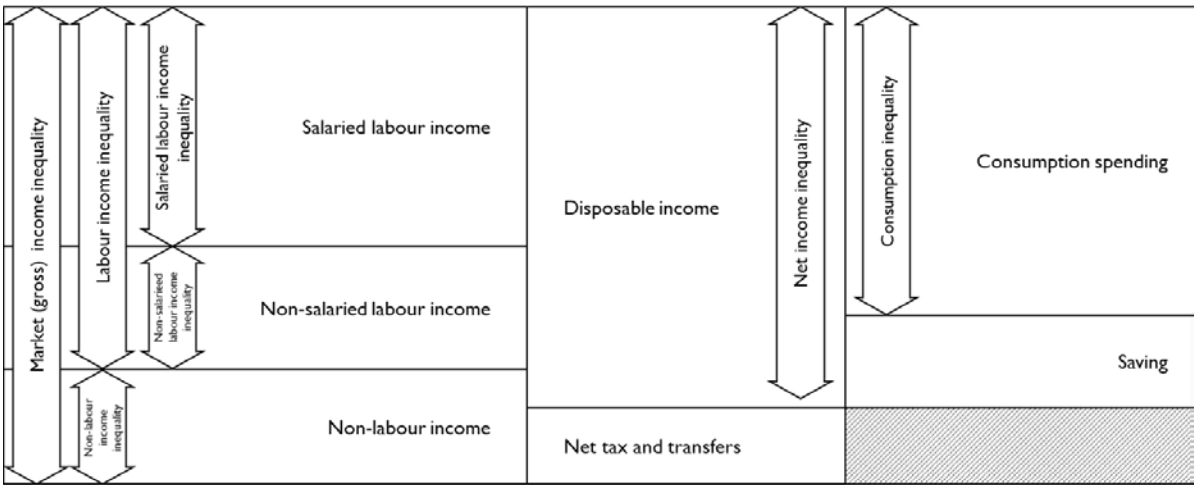
Could RBTC also be behind the rising inequality in developing economies like Indonesia? It is certainly likely. Some studies have found that routinization actually already occurs in many developing countries. For example, Maloney and Molina (2016) found evidence of 'incipient polarization' in a few countries, especially for Indonesia, Mexico, and Brazil. Reijnders and de Vries (2018) documented an increase in the share of non-routine jobs in total employment for a group of advanced and major emerging countries during the period 1999–2007, including in Indonesia. In some emerging countries, such as Brazil, Indonesia, and Mexico, they found that increase in the employment share of non-routine occupations is more than 4 percentage points. Therefore, the possibility of job polarization and routinization as the factor behind rising inequality in Indonesia is open for further study. The present paper is one attempt to do just that.

This paper's objective is to explore the extent to which labour market dynamics, including the changing nature of work (job polarization, routinization), can be a factor for the rising inequality in Indonesia. The paper starts by revisiting the development of inequality in Indonesia from 1960 to 2020. It then describes the structural transformation in Indonesia in the era before and after the AFC. The rest of the paper includes analyses using labour force survey data to explore different dimensions of labour market dynamics and links them in the context of rising inequality in Indonesia.

2 Development of inequality in Indonesia

To set the context more accurately, we first need to discuss the scope of the inequality that is measured in Indonesia. In Indonesia, the headline inequality indicator is typically measured by the Gini coefficient of expenditure or consumption per capita. It is therefore useful to understand how this expenditure is related to the other measure of inequality, namely earning (discussed in the latter part of the paper). The different components of labour and consumption inequality in Figure 1 show how these two measures are related. In any country, income may be derived from non-labour income and labour income. The labour income component can further be divided into salaried labour income and non-salaried labour income. This distinction is important in developing countries given the high informality in employment. This division is also relevant because informal (non-salaried) labour income is rarely recorded by labour force surveys. In Indonesia, informal (non-salaried) labour income is not normally recorded. Later analysis in this paper uses this measure of labour earning despite its limitations.

Figure 1: Components of labour and consumption inequality



Source: authors' interpretation.

When inequality in Indonesia is discussed in a typical academic discussion or even political discourse, it normally refers to inequality in consumption per capita. Consumption per capita is also used to calculate official poverty incidence. In this section, we discuss the development of consumption inequality in Indonesia from 1964 to 2020.[1] Later in Section 5, we discuss inequality in formal labour earning in Indonesia. We also show that inequality in formal labour earning tends to be highly correlated with inequality in consumption per capita. This strengthens the relevance of the rest of this paper.

As Figure 2 shows, from early 1960s to the end of the 1970s, inequality in Indonesia increased. One explanation is that during the same period an increase in urban workers' skills premium because of import substitution policies aimed at developing capital-intensive sectors (e.g., see Leigh and Van der Eng 2009).

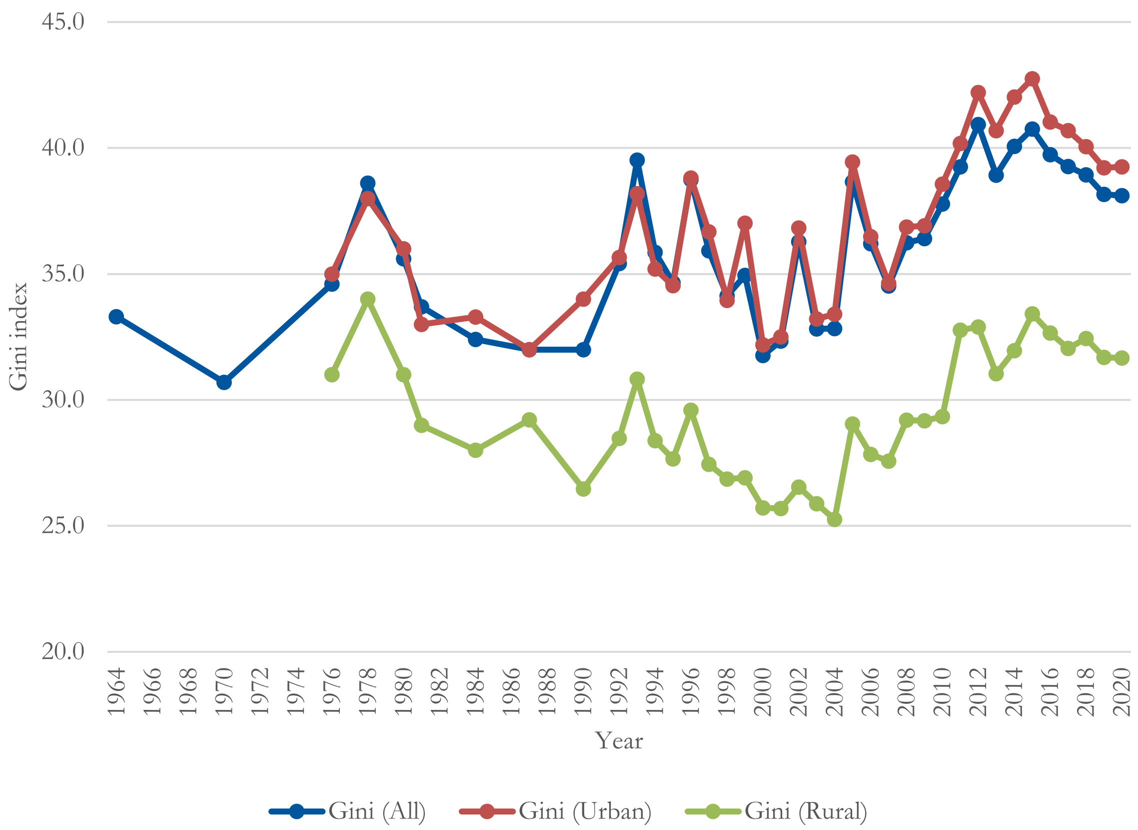
From 1980 to the end of the 1990s, before the AFC, the Gini coefficient was stable, if not slightly decreasing. However, after the AFC the Gini coefficient had a strong upward trend, evident in both urban and rural areas. The Gini coefficient after the AFC was 0.31 in 2001 but rose to 0.41 in 2013 (an increase of 0.1 or 33 per cent) in urban areas. The rate of change in rural areas is rather similar, where in 2001 the Gini coefficient was 0.24 and in 2013 it rose to 0.32 (an increase of 34 per cent). After its peak in 2012, the Gini coefficient started to show a slowly declining trend till 2019. In 2020, the Gini coefficient started to slightly rise again, most likely due to the economic crises from the COVID-19 pandemic.

Yusuf et al. (2014) pointed out that the rise in inequality during the 2000s is more notable when using the decile dispersion ratio, that is, the ratio of the top 10 per cent to the bottom 10 per cent in the distribution. From 1993 to 2013, the decile dispersion ratio tended to decline moderately before the AFC, falling even further during the AFC but increasing rapidly after the AFC up to 2013. The decile dispersion ratio trend for the 2000s suggests rising inequality that is more significant than that made visible by the Gini coefficient. For example, from 2001 to 2013, the decile ratio for all of Indonesia rose by 66 per cent or 0.40 point every year. This is quadruple the 0.13-point a year rise between 1990 and 1997. The rising decile dispersion ratio is more prominent for urban areas and in Java: in urban areas the ratio between the 10 per cent richest and the 10 per

[1] This is generally an update of Yusuf et al. (2014) and extending the work of Kim et al. (2020). Yusuf et al. (2014) cover the years from 1993 to 2013 and Kim et al. (2020) cover only up to 2017.

cent poorest from 2001 to 2013 widened by around 74 per cent. The gap between the top and bottom income groups also grew significantly in rural areas, although slower than in urban areas. As a result, during the 2000s, the rise in inequality in Indonesia has been recorded to be among the highest in the world (see Table 1).

Figure 2: Gini index of consumption, 1964–2020



Source: author's calculation based on BPS (2021).

Table 1: Change in inequality in the 2000s for top 10 countries

No.	Country	Start	End	Period	% Change	Change
1	Indonesia	33.0	39.5	2002–13	19.6	6.5
2	Serbia	32.0	38.3	2002–15	19.7	6.3
3	Rwanda	45.1	50.4	2000–13	11.8	5.3
4	United States	36.9	42.2	2002–14	14.3	5.3
5	Cameroon	42.1	46.5	2001–14	10.4	4.4
6	Austria	24.0	27.3	2001–15	13.6	3.3
7	Djibouti	40.9	44.1	2002–13	7.9	3.2
8	Spain	31.2	34.3	2002–15	10.0	3.1
9	Luxembourg	26.5	29.2	2001–15	10.2	2.7
10	Slovenia	22.1	24.6	2002–15	11.6	2.6

Source: authors' computation based on the WIID (UNU-WIDER n.d.).

Another dimension of income disparity in Indonesia that we consider in our analysis is inter-regional inequality. Yusuf et al. (2014) analysed this to check whether rising regional economic imbalance may be behind the rising inequality. They calculated the Theil index of inter-regional inequality that is one of the most common measures used to estimate inter-regional inequality. The Theil index was calculated for both inter-provincial inequality and inter-district inequality. Yusuf et al. (2014) found that there is no tendency towards increasing inter-regional disparity in Indonesia. In fact, inequality in Indonesia is driven primarily (e.g., 93.7 per cent in 2013) by within-province inequality. Inequality between provinces only contributes to 6.3 per cent of the overall inequality. Similar patterns are evident in urban–rural groups. Only a slight proportion (5.8 per cent in 2013) of overall inequality can be attributed to inequality between urban and rural areas. The largest contribution is inequality within urban and rural areas. The analysis suggests that the contribution of inequality between provinces and between urban and rural areas has been consistently declining since 1993. Conversely, the contribution of inequality of individual households within provinces and within urban and rural areas is consistently increasing. In short, the rising inequality in Indonesia has been common or uniform across geographical locations, whereas the gap between regions is rather stable or slightly declining in more recent years.

The causes of recent changes in inequality in Indonesia are complex but it is possible to identify a set of specific factors[2] with sufficient empirical evidence that would be worthy of future exploration. The first factor is related to trade. Indonesia has experienced a commodity boom in coal and palm oil, and this has had an impact on inequality: Yusuf (2014) used a computable general equilibrium model to show that the changes in inequality are due to world prices of mining commodities rather than estate crops. Relatedly, the commodity boom hypothesis could be advanced to explain the widening gap between poor and rich groups in rural areas.

During more or less the same period, there has been a trend towards the increase in the price of commodities, particularly those that are traditionally Indonesian export commodities such as estate crops. Those estate crops are mainly located in rural areas and are owned by landowners in rural areas. The richer households in rural areas benefit from this commodity boom disproportionately. One way to see this mechanism at work is to look at the evolution of inequality in rural areas distinguished by Java and non-Java islands because estate crop plantations are mostly located outside Java. The weakness of this argument is that it cannot explain the uniformity of rising inequality in all regions in Indonesia. Inequality increase seems to change everywhere, both in resource-rich and in not-so-resource-rich regions.

A second factor is that of domestic prices of rice. One inequality spike is that which occurred in 2003–05. There are various possible reasons why inequality rose sharply from 2003 to 2005. The domestic price of rice increased by almost 20 per cent during this period after being very stable for a long period. This may have reduced the real expenditure of the poor.

A third factor is related to changes in the labour market and fiscal policy in Indonesia. Yusuf et al. (2014) argue that changes in the formal labour market including interrelated changes in labour market regulation—an increase in severance payment, the strengthening of labour unions, rising minimum wages, reduced demand for unskilled labour, and an increase in informality in lower-wage employment—have had an impact on inequality in skilled and unskilled urban and rural sectors. Before the AFC, the manufacturing sector was the primary source of economic growth in Indonesia. The gross domestic product of the manufacturing sector was 11.2 per cent during 1990–96 (while the average economic growth was 7.9 per cent) and its employment growth was 6 per cent (while the average national employment growth was only 2.3 per cent). Almost a decade after the crisis, the role of the manufacturing sector in generating employment seems to have halted. Its economic growth for the period 2000–08 was almost the same as the national average

[2] The global literature has identified a set of factors that drive expenditure inequality (UNDP 2014). One way of grouping these is as exogenous and endogenous drivers. The former relates to shifting global trade and finance patterns and technical change. The latter pertains to macroeconomic policies, labour market polices, wealth inequality, fiscal policy (taxation and transfers), and government spending on public goods.

(4.7 per cent), but its employment growth was only 0.9 per cent. The employment opportunities in the formal manufacturing sector, historically, have been a haven for people in rural areas to find better paying livelihoods. When such opportunities are limited, there is an excess supply of unskilled labour in rural areas. As the labour market in rural areas is more flexible, overall rural real wages are pushed down as a consequence of increasing inequality in rural areas. This may indicate a possibility of constraints for people to migrate to cities and find formal employment (Manning and Pratomo 2013).

A fourth factor is large transfers, notably rice and fuel subsidies. During the inequality spike of 2003–05 world oil prices rose by 70 per cent, leading to an increase in fuel subsidies from 6.5 per cent of the total government budget in 2003 to almost 16 per cent in 2005. This meant that the fiscal space for additional government social spending was curtailed and the benefit of the fuel subsidy disproportionately benefited the non-poor. In October 2005, the Indonesian government made a large adjustment to fuel prices, increasing retail fuel prices for gasoline, kerosene, and diesel. The price of gasoline increased by 87.5 per cent, diesel by 104.7 per cent, and, surprisingly, kerosene by 185.7 per cent (Yusuf and Resosudarmo 2008). The Indonesian government also distributed cash transfers of 18 trillion Indonesian rupiah to the poor and the near-poor to mitigate the inflationary effect of the price increase at that time. This policy package likely contributed to the decline of the Gini coefficient from March 2005 to March 2006. However, the Gini coefficient started rising steadily again thereafter.

A fifth and last, but not least, factor that may be related to the changing inequality in Indonesia is structural transformation. This is, perhaps, one of the most plausible explanations, given that inequality is rather slow to change over time. The changing inequality in Indonesia is rather fast by historical standards and, as Henry Aaron, the American economist, said in the 1970s, observing inequality is like 'watching the grass grow',[3] structural transformation may be just the big driver that is behind this. This is explored in more detail in the next section.

3 Structural transformation

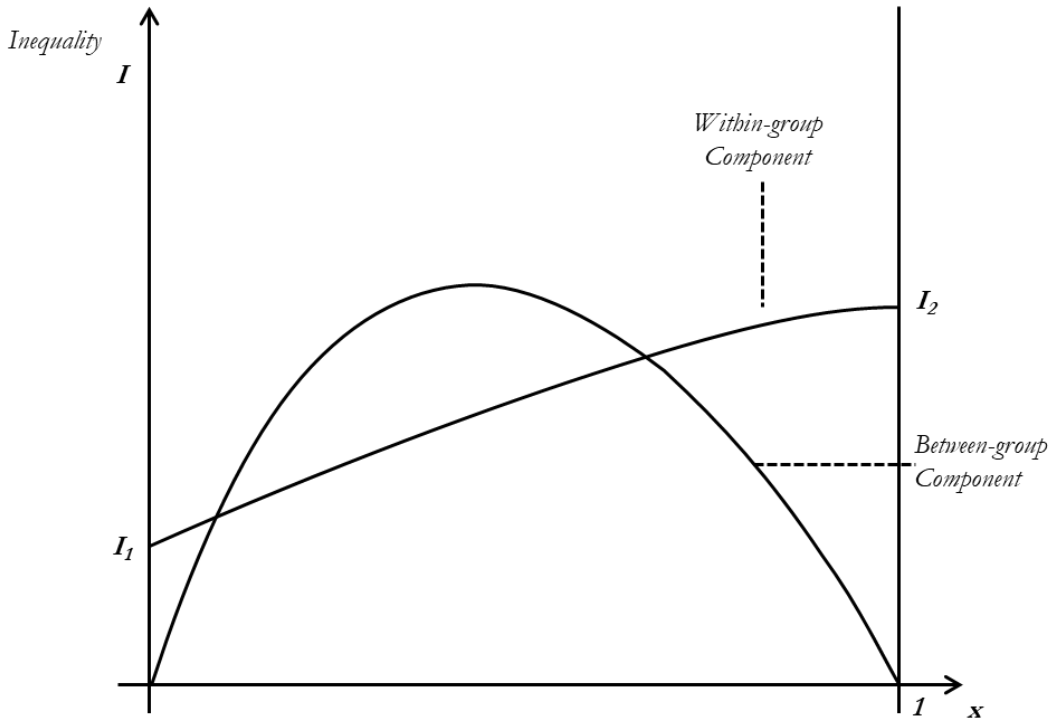
The relationship between structural transformation and inequality is best described by the Kuznetsian process that is nicely illustrated in Anand and Kanbur (1993). As shown in Figure 3, the Kuznets process can be represented by decomposing between-sector (or group) inequality and within-sector (or group) inequality, each of which contributes to overall inequality.

Suppose we define inequality (I) to be the overall measure of inequality in a given country and x to be the share of labour in the non-agricultural sector. Let us assume that there is only one non-agricultural sector and the working population is normalized to one. We can then define between-sector inequality as the inequality in the income distribution when a fraction x of the population receives income μ_1 and the remaining fraction, $1-x$, receives income μ_1. Between-sector inequality is defined as the value of the index of inequality when everyone in the sector receives the mean income of that sector. Kuznets assumed, the mean income of the non-agricultural sector is higher than that of the agricultural sector or $\mu_1>\mu_2$. At both $x=0$ and $x=1$, inequality must be zero. When $0<x<1$, inequality will first increase with increasing x, then decrease as x increases. This is because when x is low, there is more labour in agriculture than in non-agriculture, so that between-sector inequality is high. However, when more and more workers are in non-agriculture, between-sector inequality starts falling. It continues falling until it reaches zero when all workers are in the non-

[3] As quoted in Myles (2003).

agricultural sector. How within-group inequality (the difference between overall inequality and between-group inequality) changes with the increase in x depends on the assumptions about which sector is more unequal. If we assume that within-group inequality in the non-agricultural sector is higher than in the agricultural sector, then the within-group inequality component of overall inequality will increase as x increases.

Figure 3: The Kuznets process

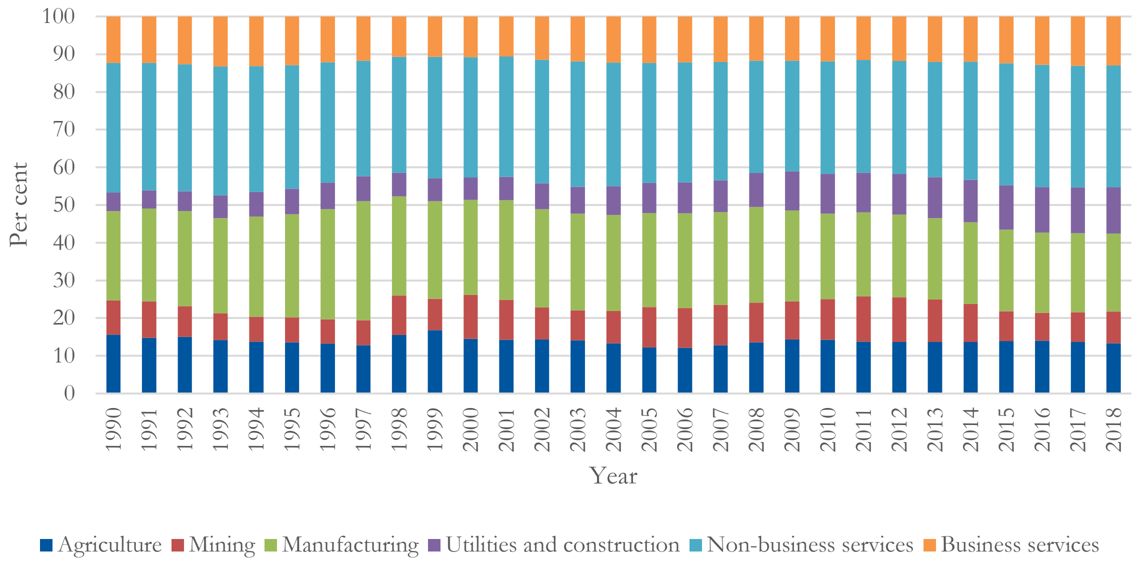


Source: reproduced from Baymul and Sen (2020), under the Creative Commons license CC BY-NC-ND 4.0.

From 1990 to 2018, as shown in Figure 4, industrialization (the rising share of manufacturing value added) occurred since 1990 until 1997, before the AFC. The share of manufacturing value added changed from 19.3 per cent in 1990 to 22.5 per cent in 1997. Its employment share also increased from 10.3 to 13.2 per cent (Figure 5). Employment in non-business service sectors also rose from 30 to 38 per cent in 1997, yet the value added by non-business sectors did not change much. It seems that employment in the agricultural sector moved to almost all non-agricultural sectors, including manufacturing and services. In this period, the change in inequality was not significant. Kim et al. (2020) named this period as benign or weak Kuznetsian tension: a period of strong growth-enhancing structural transformation, yet stable or declining inequality.

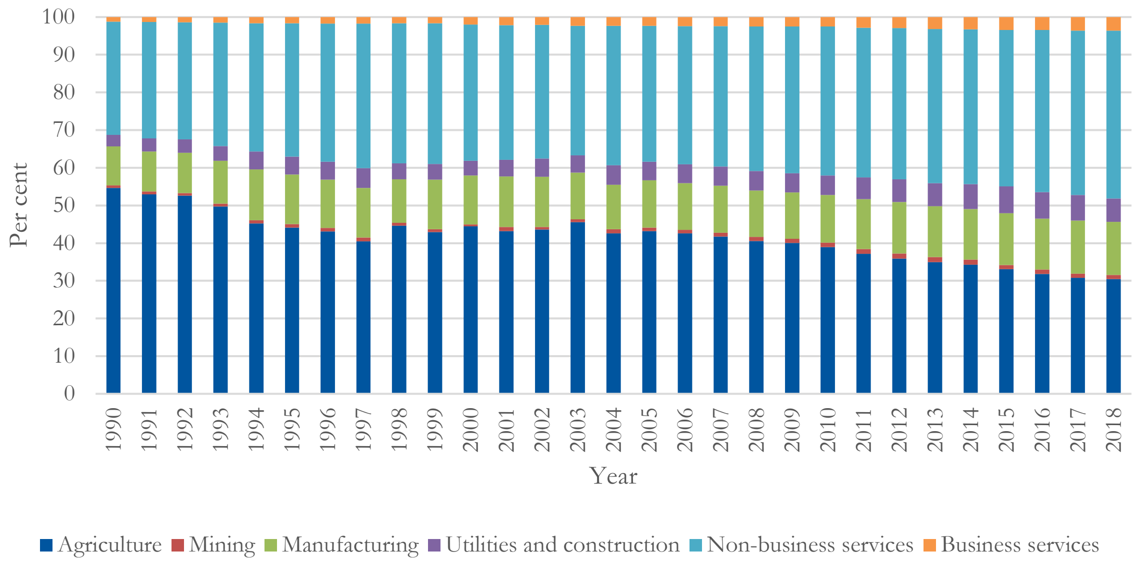
As discussed in Kim et al. (2020), Indonesia avoided the Kuznetsian tension during the 1990s because of some probable factors. As noted by Leigh and Van der Eng (2009), with large public expenditure and investment in rural development, agricultural productivity improved with a large increase in agricultural employment to help rural development. The expansion of labour-intensive manufacturing from the mid-1980s also generated a substantial number of jobs. This is consistent with Baymul and Sen (2020) who showed empirically that the movement of workers away from agriculture is unambiguously related to an increase in inequality, yet there is no Kuznets-type relationship between the share of manufacturing employment and inequality when the different paths of industrialization are considered; in fact, increasing the share of workers in the manufacturing sector tends to decrease inequality in Africa and Asia.

Figure 4: Composition of value added (%), 1990–2018



Source: authors' calculation based on GGDC/UNU-WIDER Economic Transformation Database (de Vries et al. 2021).

Figure 5: Composition of employment (%), 1990–2018



Source: authors' calculation based on GGDC/UNU-WIDER Economic Transformation Database (de Vries et al. 2021).

After the AFC, however, the rising trend of the manufacturing sector's value added seems to halt. The share of the manufacturing sector's value added in 2018 (21.4 per cent) was still lower than the share in 1997 (22.5 per cent). The share of its employment also stayed the same. As employment in agriculture continued to fall, service sectors absorbed most of the labour from agriculture. During the 2000s, Indonesia experienced a stalled industrialization and tertiarization.

The period of stalled industrialization was accompanied by unprecedented rising inequality. Kim et al. (2020) have described what happened in Indonesia during this period as the period of adverse Kuznetsian tension; that is, a period of weak growth-enhancing structural transformation accompanied by increasing inequality.

4 Within- and between-sector inequality: the Kuznetsian dynamics

As explained previously, at the centre of the Kuznets theory is how inequality changes as an economy's sectoral share of employment changes and how overall inequality is affected by the difference of inequality between and within sectors[4] (see Anand and Kanbur 1993; also see Figure 3). The analysis in this section further examines the evidence within the same framework. We need an indicator of inequality that can be used to check this. To do this, we use the Atkinson index of inequality because of its decomposability into between and within inequality. We look at the evolution of inequality over the period 1992–2020. The Atkinson index of inequality was proposed by Atkinson (1970). To calculate the inequality index,[5] let us define a population of household i=1, 2, …, N with income y_i. According to Atkinson (1970), y^{EDE} is the equally distributed equivalent income, which can be calculated from the data as:

$$y^{\mathrm{EDE}} = \begin{cases} \left(\frac{1}{N}\sum_{i=1}^{N} y_i^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}} \text{ for } 0 < \varepsilon \neq 1 \\ \left(\prod_{i=1}^{N} y_i\right)^{\frac{1}{N}} \text{ for } \varepsilon = 1 \end{cases} \tag{1}$$

Then, the Atkinson index is defined as:

$$A(\varepsilon) = 1 - \frac{y^{\mathrm{EDE}}}{\mu} \tag{2}$$

where μ is the arithmetic mean of y_i and ε is a parameter for the degree of inequality aversion. The well-known property of the Atkinson index of inequality is that it is decomposable by between-group and within-group components. Therefore, we can estimate the contribution of within-group and between-group inequality to overall inequality. The Atkinson index can be decomposed into within-group inequality I_W and between-group inequality I_B,[6] where

$$I_W = 1 - \frac{1}{\mu}\sum_{k=1}^{K} \frac{N_k}{N} y_k^{\mathrm{EDE}} \tag{3}$$

and

$$I_B = 1 - \frac{y^{\mathrm{EDE}}}{\sum_{k=1}^{K} \frac{N_k}{N} y_k^{\mathrm{EDE}}} \tag{4}$$

where k=1, …, K is the sub-group k of the population, N_K is the number of population in group K, and y_k^{EDE} is the equally distributed equivalent income of group k. A decomposition analysis is used to estimate the contribution of within-sector and between-sector inequality to overall inequality and to understand how the proportion of each contribution changes over time.

Consideration of inequality within different economic sectors and how inequality within sectors evolves over the course of structural transformation are important in understanding how structural

[4] This is an extension of the work in Yusuf et al. (2021) by expanding the year's coverage into 2020.

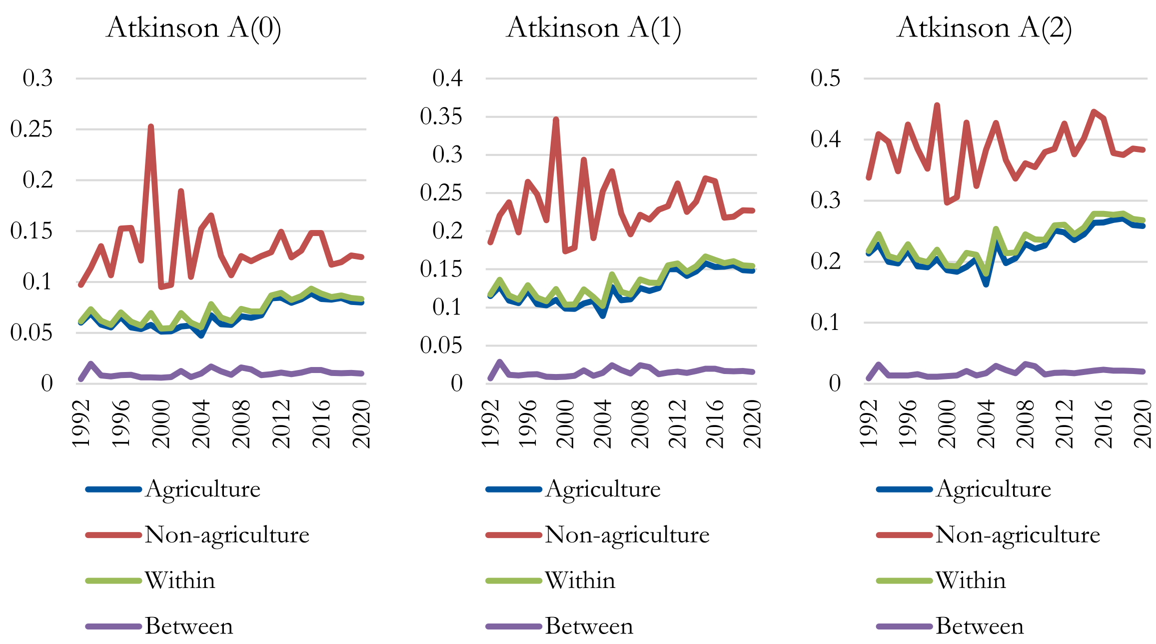
[5] This formulation of the Atkinson index is based on the explanation in the manual of the STATA software, in which its routine *ineqdeco* is used to practically implement the decomposition written by Jenkins (1999). The *ineqdeco* command from STATA is used to do the decomposition.

[6] Note that the index is decomposable but not additively decomposable.

change and inequality co-evolve. This process is at the heart of the classical Kuznetsian theory of structural transformation. Kuznets (1955, 1973) hypothesized that inequality rises in the early stages of structural transformation because labour moves from a relatively equal sector (e.g. agriculture) to relatively less equal sectors (e.g. manufacturing), and, as a consequence of this process, overall inequality rises. We analyse this in the Indonesian case using district-level data. We measure consumption inequality (Indonesian headline inequality indicator) within and between economic sectors using the distribution of expenditure per person within each sector and the sector of employment of the head of the household. The data used here are the same as Indonesian official statistics data used to calculate the Gini coefficient, that is, the National Socio-Economic Household Survey (*Survei Sosial Ekonomi Nasional*, SUSENAS).

The decomposition of inequality by economic sector using the Atkinson index of inequality additionally helps to explain what happened to inequality within the context of structural transformation. Figure 6 shows the sectoral decomposition of the Atkinson index of inequality from 1992 to 2020, with different alpha parameters 0, 1, and 2.

Figure 6: Sectoral decomposition of the Atkinson index of inequality



Source: authors' calculation.

As shown in Figure 6, first, inequality in Indonesia started rising during the 2000s through the stalling industrialization/rapid tertiarization period, in particular, during the mid-2000s. This confirms earlier observation using more standard inequality measures such as the Gini coefficient. The Atkinson A(1) index shows that Indonesian consumption inequality increased by 23 per cent from 1992 to 2020. However, there are two discernible periods: (1) the rapid industrialization period (1992–97), when consumption inequality actually stayed virtually the same; and (2) the stalling industrialization/rapid tertiarization period (2001–20), when consumption inequality increased (by 48 per cent).

Second, the largest contributor to rising inequality in Indonesia overall is the change in inequality within sectors, and certainly not inequality between sectors. From 2001 to 2020, the Atkinson A(1) index for Indonesia overall increased by 48 per cent, and 90 per cent of the increase was due to the increase in the within-sector component of inequality. During the 2000s, labour moved from agriculture to non-agriculture (mostly services); yet, not as expected by Kuznets, inequality between the agricultural and non-agricultural sectors basically stayed the same and the inequality within the agricultural and non-agricultural sectors rose. The result was the overall increase in inequality.

In sum, in the process of structural transformation in Indonesia during the sample period, labour moved from agricultural to non-agricultural sectors. Yet, there are two distinct periods that mark the transformation. During the rapid industrialization period (1992–97), there was substantial labour movement to industry, specifically to the manufacturing industry. During the stalling industrialization/rapid tertiarization period (2000–20), the share of labour in manufacturing was steady and more labour moved to the services sectors. We find that structural transformation during the rapid industrialization period is not accompanied by overall rising inequality, unlike the structural transformation during the stalling industrialization/rapid tertiarization period. In short, the Kuznets hypothesis connecting income inequality and structural change holds in the later period but not in the former. Further, rising inequality is evident in all sectors of the economy, including the sector that much labour moved from: agriculture. Moreover, the rate of increase in inequality within the agricultural sector is much faster than within the non-agricultural sector. The Kuznets hypothesis does not explicitly predict this. When we disentangle the non-agricultural sector, we find that there are certain sub-sectors within the services sectors where labour from the agricultural sector moves to, for example, non-business services, which experience a dramatic fall in inequality in the earlier period (1992–97), but a dramatic rise in the later period. Finally, within-sector inequality is the largest contributor to rising inequality in Indonesia after the AFC. In the next section, we go into deeper analysis of the sub-topic within structural transformation, that is, labour market dynamics.

5 Labour market dynamics and earnings inequality

5.1 Data and mapping task content to occupation

In this section, we use the National Labour Force Survey (*Survey Angkatan Kerja Nasional*, SAKERNAS), a nationally representative survey of labour force in Indonesia. Statistics Indonesia (*Badan Pusat Statistik*, BPS) has been conducting the survey since 1976. In the early years, it was a quarterly survey; it became annual in 1994, and then semi-annual in 2006 (Dong 2016). The SAKERNAS sample size varies from year to year, with recent rounds being the largest.

The objective of SAKERNAS is to collect information on Indonesia's workforce and capture any changes in its structure. SAKERNAS covers all provinces of Indonesia, with some exceptions for remote provinces in certain years. The sample size of SUSENAS, particularly those of recent surveys, represents Indonesian districts, and the sample size of older surveys only represents provinces. SAKERNAS selects enumeration areas from the census sampling frame, choosing segment groups within the enumeration areas and interviewing all households in the segment groups. Within each household, the household head (typically) answers questions about household members aged 10 years and older. At the individual level, SAKERNAS collects the highest level of education completed, working status, employment sector, industry and occupation of employment, working hours, and earning for wage earners. Until 2014, earning data were only collected for salaried workers; since then, earning data for self-employed workers are also collected.[7]

For this study, we have SAKERNAS data from 1994 to 2017. However, workers' occupation type was only recorded since 2001. Moreover, the standard coding for occupation variables varies from year to year and is presented in Table 2. The International Standard Classification of Occupations (ISCO) code of most SAKERNAS data (2001–07 and 2012–15) is based on ISCO-68. We only have the data for 2008–10 (3 years) with occupation data based on ISCO-88.

Table 2: National Labour Force Survey (SAKERNAS) of Indonesia

Year	Occupation code	Level
1994–99	No	No
2000	ASCO-97	3-digit
2001–06	ISCO-68	3-digit
2007–10	ISCO-88	4-digit
2011–12	ISCO-68	1-digit
2013–15	ISCO-68	3-digit
2016–18	ISCO-68	1-digit

Source: authors' elaboration based on World Bank (2014).

Based on the above constraint, while maximizing the duration for the analysis, we choose four different years for the analysis: 2001, 2005, 2010, and 2015. For this study, we cannot use the data without the occupation code or with only a one-digit occupation code.

We combine SAKERNAS with the O*NET (2003) database and map each occupation with the measure of the intensity of various tasks. The O*NET database provides task contents for occupations for the United States economy using the Standard Occupational Classification (SOC-00). These tasks are divided into four broad categories: (a) non-routine cognitive analytical, (b) non-routine cognitive interpersonal, (c) routine cognitive, and (d) routine manual. The difference between these four types of tasks is summarized in Table 3. The first year that the survey recorded labour occupational classification was in 2001. The last year that the survey included job classification by more than one digit was in 2015, which we explain later.

Table 3: Types of tasks

Non-routine cognitive analytical ($nr_{analytical}$)	Non-routine cognitive interpersonal ($nr_{personal}$)	Routine cognitive ($r_{cognitive}$)	Routine manual (r_{manual})
• Analysing data/information • Thinking creatively • Interpreting information for others	• Establishing and maintaining personal relationships • Guiding, directing, and motivating subordinates • Coaching/ developing others	• Importance of repeating the same tasks • Importance of being exact or accurate • Structured versus unstructured work (reverse)	• Pace determined by the speed of equipment • Controlling machines and processes • Spending time making repetitive motions

Source: adapted from Table 2.1 in Ridao-Cano and Bodewig (2018: 67).

Occupation mapping for Indonesia is conducted by matching each occupation in SAKERNAS to the task measures derived from the O*NET database following the methodology employed by

[7] See Dong (2016) for an evaluation of SAKERNAS data in comparison to other popular survey data of the Indonesian Family Life Survey.

Acemoglu and Autor (2011) that uses ISCO-88. Based on the data, only SAKERNAS 2010 is structured on ISCO-88 with a four-digit level of detail. Therefore, we conduct the initial mapping for SAKERNAS 2010 with O*NET using the method developed by the Institute for Structural Research (*Instytut Badan Strukturalnych*, IBS 2016).

SAKERNAS uses different ISCO codes from year to year and its detailed digit level also differs across years. For the years 2001–07, SAKERNAS used ISCO-68 with a three-digit level of detail. For the years 2008–11, SAKERNAS changed to ISCO-88 with a four-digit level of detail. For 2012–15, it changed again to ISCO-68 with a three-digit level of details. From 2016 onwards, only one-digit level of ISCO-68 can be identified from the data. Thus, we convert ISCO-68 of SAKERNAS into ISCO-88. This is only possible if we aggregate the occupations into two-digit classifications only.

Following Autor and Dorn (2009, 2013), we calculate a single measure of routine-task intensity (RTI) based on the four different types of tasks:

$$RTI = \ln\left(\frac{r_{\text{cognitive}} + r_{\text{manual}}}{2}\right) - \ln\left(\frac{nr_{\text{analytical}} + nr_{\text{personal}}}{2}\right) \tag{5}$$

As the RTI measure (which we call O*NET RTI) is based on United States SOC-00, country heterogeneity is not allowed. Lewandowski et al. (2019) showed that the same job can have different skill requirements in countries with different income levels. Lewandowski et al. (2020) found that similar work in low- and middle-income countries was carried out more regularly than in high-income countries. To complement the measure, we also use a special measure of RTI specific for Indonesia (country-specific RTI) created by Lewandowski et al. (2020).

5.2 Results

Earnings inequality

Our first analysis is to check how inequality in earnings changes over time. Table 4 shows inter-quantile ratios and inequality indices for 2001–15. The Gini coefficient of real earning increased from 0.38 in 2001 to 0.48 in 2015, a more than 25 per cent rise in just 14 years. Between 2001 and 2015, the rise is almost 30 per cent (29.7 per cent). However, when we look at the inter-quantile ratio, particularly the ratio between the 10th decile and the 1st decile, the rise in inequality during the same intervening years is larger. For example, the increase in the inter-quantile ratio (90/10) between 2001 and 2015 is 33 per cent, and between 2005 and 2015 is 43 per cent. It confirms that the rising earnings inequality between these two year ranges, particularly between 2005 and 2015, is caused by the disproportionate rise of the top 10 per cent of earners.

Table 4: Inter-quantile ratios and inequality indices

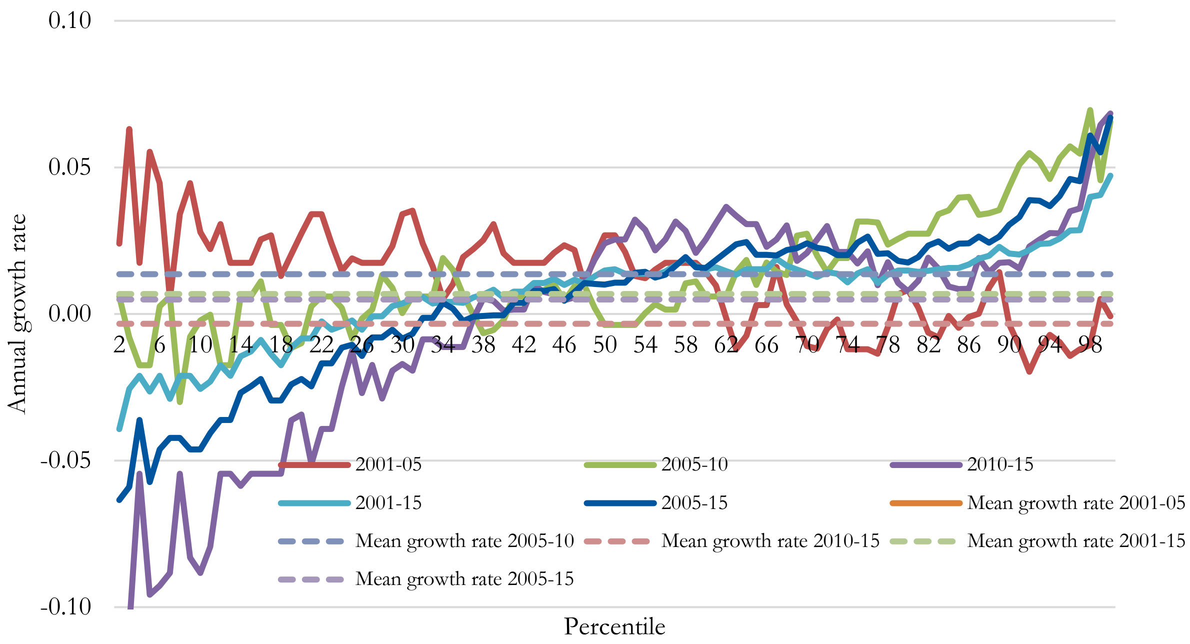
	Inter-quantile ratios					Inequality indices			
	2001	2005	2010	2015		2001	2005	2010	2015
ln(q90)–ln(q10)	1.83	1.70	1.95	2.44	Var (log earn)	0.55	0.49	0.61	0.92
ln(q90)–ln(q50)	0.91	0.76	1.03	0.98	Gini (log earn)	0.03	0.03	0.03	0.04
ln(q50)–ln(q10)	0.92	0.93	0.92	1.46	Gini (earn)	0.38	0.37	0.42	0.48

Source: authors' calculation.

As discussed earlier in this paper, despite formal labour earnings constituting only some part of the headline consumption inequality in Indonesia, the trend of the inequality of the labour earning turns out to be consistent with the trend of consumption inequality. To recall, the Gini coefficient of consumption right after the AFC (2001) was 0.31 but rose to 0.41 in 2013 (an increase of 33 per cent). The rise in the inequality during the 2000s is more notable when using the decile dispersion ratio, that is, the ratio of the top 10 per cent to the bottom 10 per cent in the distribution. From 2001 to 2013, the decile dispersion ratio for all of Indonesia rose by 66 per cent or 0.40 point every year. This consistency is quite relieving because it presents the opportunity to explore further the notion that the increase in consumption inequality in Indonesia, to a large extent, may have to do with labour market dynamics, particularly the rise in formal labour earnings inequality.

We confirm the rising inequality of earnings by showing the growth incidence curve of labour earnings for various years to understand what is behind the changing inequality between time periods (Figure 7).

Figure 7: Growth incidence curves, 2001–15



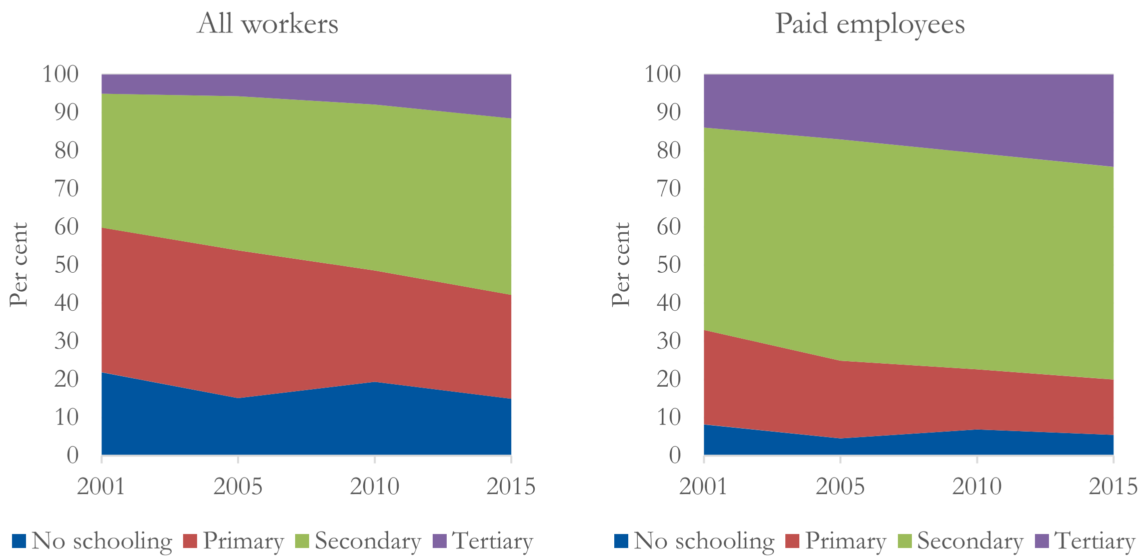
Source: authors' calculation.

It is clear from Figure 7 that, except for the period 2001–05, the slope of the growth incidence curve is generally positive, particularly for the period 2005–15. The positive slope of the growth incidence curve—that is, the proportionate increase in higher-wage workers (initially) being larger than the proportionate increase in lower-wage workers—indicates a rising inequality between the intervening periods. It should be noted, however, that in the period of rising inequality (positive slope of the growth incidence curve), such as 2005–15, the annual growth rate of real earning of lower-wage workers has been negative. Their increase in the nominal salary cannot cope with the rising cost of living (consumer price index). From this we can conclude that earnings inequality in general rises in the same direction as consumption inequality, or the Indonesian headline indicator for inequality. This may suggest that labour market dynamics is a plausible driver of the rising inequality in Indonesia, a satisfactory explanation of which is yet to be settled. The next section explores the development of other dimensions of labour market dynamics that may be probable factors behind these remarkable increases in inequality.

Education

Next, we look at the education attainment of these workers and explore trends that can potentially be related to the rising earnings inequality. Figure 8 shows the distribution of workers by education level for all workers (on the left) and for only salaried workers (on the right). Both categories show the declining share of workers with primary education and below and the increasing share of workers with secondary and tertiary education. For example, for the category of paid employees, the share of workers with primary education declined from 38 per cent in 2001 to 27 per cent in 2015, whereas the share of those with secondary education rose from 35 to 46 per cent for the same years, respectively, an increase by 11 percentage points.

Figure 8: Workers distribution by education level



Source: authors' calculation.

The dynamics is slightly different among salaried workers. The share of workers with primary education or below declines in a similar manner. Between 2001 and 2015, the share of workers with primary education fell by 10 percentage points, almost the same as with all workers (10.7 per cent). However, the increase in the share of workers with secondary education only rose by 2.7 percentage points, in contrast to an increase by 11 per cent among all workers. What makes it all different is the increase in the share of workers with tertiary education among salaried workers. The share of workers with tertiary education, among salaried workers, rose from 13.9 per cent in 2001 to 24.2 per cent in 2015, an increase by 10.3 percentage points.

We also estimated education premium by gender and education level for 2001, 2005, 2010, and 2015. We estimated the standard Mincerian earning equation for all salaried workers controlling for age (as a proxied for experience) as well as regions. We report only the estimate of the coefficient of the education level that represents a return to education in Figure 9. The higher the education premium, the higher the level of education. For men, for example, return to tertiary education (1.18) is more than twice the return to secondary education (0.48) in 2015. Except for return to primary education, the return to education for women is considerably lower than that for men. For secondary education, women's return to education is 0.69 compared with 0.48 for men. Thus, for secondary school graduates, return to education for women is 44 per cent higher than that for men. Overall, return to education (in 2015) is the highest for female workers with tertiary education.

In summary, we establish two important facts that may help identify factors behind the rising earnings inequality. First and foremost, we observe a disproportionate increase in the returns to tertiary education. This naturally has a tendency towards increasing inequality. Second, the increasing share of workers with tertiary education may also be accompanied by rising inequality. We explore this further in a later section.

Figure 9: Education premium by gender and education level

Source: authors' calculation.

Employment status composition

Changing employment status, particularly from unpaid (informal) to paid/salaried (formal) employment is relevant particularly when we want to establish a good connection between earnings inequality and headline consumption inequality. The more labour becomes formal, the more formal earnings inequality becomes relevant.

Table 5 shows the share of labour by different employment status for the years 2001, 2005, 2010, and 2015 and Table 6 shows the share of workers by sector. The share of salaried workers increased from 30.25 per cent in 2001 to 40.15 per cent in 2015. Similar increase is also observed for both male and female workers. Except for the share of casual employees, which shows an increase or remains stable during the same period, it seems that the declining share of all other less informal workers contributes to the increase in the share of salaried workers.

The increasing trend of the share of salaried workers not only heightens the relevance of rising earnings inequality in the context of overall (headline) consumption inequality in Indonesia; when combined with other trends such as the rising share of tertiary education within formal worker groups, it also may actually have direct consequences on overall earnings inequality and to some extent on overall consumption inequality. Of course, this needs further empirical analysis.

Table 5: Distribution of workers by employment status (per cent)

	2001	2005	2010	2015
All workers				
Paid employees	30.25	28.73	31.12	40.15
Self-employed without employees	19.21	18.59	19.11	16.42
Self-employed with temporary/unpaid worker	21.41	21.12	18.5	14.55
Self-employed with permanent worker	3.01	2.89	2.92	3.38
Casual employee in agriculture	4.01	5.83	5.46	4.43
Casual employee not in agriculture	2.75	4.75	5.01	6.77
Unpaid worker	19.37	18.08	17.89	14.3
Male workers				
Paid employees	26.04	26.93	29.35	37.36
Self-employed without employees	16.65	15.01	16.84	16.47
Self-employed with temporary/unpaid worker	12.34	11.98	11.58	9.78
Self-employed with permanent worker	1.03	1.15	1.27	1.74
Casual employee in agriculture	4.43	5.57	4.95	3.82
Casual employee not in agriculture	1.15	2.17	1.98	2.49
Unpaid worker	38.36	37.19	34.03	28.34
Female workers				
Paid employees	32.71	29.69	32.2	41.8
Self-employed without employees	20.72	20.5	20.49	16.39
Self-employed with temporary/unpaid worker	26.71	25.99	22.71	17.4
Self-employed with permanent worker	4.17	3.82	3.92	4.36
Casual employee in agriculture	3.77	5.98	5.76	4.8
Casual employee not in agriculture	3.69	6.12	6.84	9.32
Unpaid worker	8.25	7.91	8.08	5.93

Source: authors' calculation.

Table 6: Distribution of workers by sector (per cent)

Sector	All workers				Paid employees			
	2001	2005	2010	2015	2001	2005	2010	2015
Agriculture	42.49	42.47	36.98	31.34	10.64	8.33	8.03	7.86
Mining	1.07	0.99	1.20	1.16	1.47	1.44	1.79	1.62
Manufacturing	13.53	13.03	13.21	13.63	28.44	29.81	23.33	22.93
Other industry	4.42	5.12	5.59	7.67	7.55	7.29	6.52	7.70
Services	38.49	38.33	43.02	46.20	51.91	53.10	60.33	59.89

Source: authors' calculation.

Occupational structure

Table 7 shows the changing occupational structure of employment from 2001 to 2015. Over this period, we note several long-term (14 years) trends.

Table 7: Employment share and mean weekly earning by main occupational groups

	Paid employees								
	Level				Percentage growth (annual)				
	2001	2005	2010	2015	2001–05	2005–10	2010–15	2001–15	2005–15
Panel A: Share of employment (%)									
1 Managers	1.35	1.48	2.78	2.56	2.3	13.4	–1.6	4.7	5.6
2 Professionals	10.12	11.04	14.26	13.02	2.2	5.3	–1.8	1.8	1.7
3 Technicians and associate professionals	4.83	5.55	5.83	8.69	3.5	1.0	8.3	4.3	4.6
4 Clerical support workers	13.58	12.34	13.9	10.83	–2.4	2.4	–4.9	–1.6	–1.3
5 Services and sales workers	9.02	11.93	14.33	12.81	7.2	3.7	–2.2	2.5	0.7
6 Skilled agriculture, forestry and fishery	1.44	0.99	0.78	1.52	–8.9	–4.7	14.3	0.4	4.4
7 Craft and related trades workers	23.88	24.06	12.9	13.74	0.2	–11.7	1.3	–3.9	–5.4
8 Plant and machine operators and assemblers	15.67	15.39	10.58	11.88	–0.4	–7.2	2.3	–2.0	–2.6
9 Elementary occupations	20.12	17.22	24.63	24.94	–3.8	7.4	0.3	1.5	3.8
Panel B: Mean weekly earnings (constant 2010 prices)									
1 Managers	1,073,359	952,189	1,215,762	1,421,598	–3.0	5.0	3.2	2.0	4.1
2 Professionals	618,222	569,668	622,153	681,310	–2.0	1.8	1.8	0.7	1.8
3 Technicians and associate professionals	602,147	617,884	730,983	873,998	0.6	3.4	3.6	2.7	3.5
4 Clerical support workers	541,256	539,114	590,770	642,021	–0.1	1.8	1.7	1.2	1.8
5 Services and sales workers	363,798	363,351	381,087	403,862	0.0	1.0	1.2	0.7	1.1
6 Skilled agriculture, forestry and fishery	300,052	278,641	291,266	272,254	–1.8	0.9	–1.3	–0.7	–0.2
7 Craft and related trades workers	322,347	336,756	321,385	420,641	1.1	–0.9	5.5	1.9	2.2
8 Plant and machine operators and assemblers	349,374	362,758	438,672	400,295	0.9	3.9	–1.8	1.0	1.0
9 Elementary occupations	234,875	261,916	290,705	343,789	2.8	2.1	3.4	2.8	2.8

Source: authors' calculation.

We note that in 2001 most Indonesian workers belonged to the occupation group of craft and related trades (23.9 per cent), followed by elementary occupations (21.1 per cent). Managers and skilled agriculture, fisheries and forestry had the smallest share (1.35 and 1.44 per cent, respectively) of workers in the same year. In 2015 (14 years later), the largest share of workers belonged to elementary occupations (24.9 per cent), followed by craft and related trades (13.7 per cent). The share of professionals increased from 10.12 per cent in 2001 to 13.2 per cent in 2015.

We observe the increasing share of highly skilled employment (most notably professionals, services and sales workers, technicians and associate professionals) as well as the increasing share of elementary occupations. This is a sign of job polarization. We also observe the declining share of craft and related trades workers, skilled agriculture, fisheries and forestry, and managers. We find a relatively constant share of plant and machine operators and assemblers and clerical support workers. In other words, the decline in the share of occupation occurs, generally, around the middle skill level, such as clerical support workers (declines from 13.6 per cent in 2001 to 10.8 per cent in 2015) and plant and machine operators and assemblers (declines from 15.7 per cent in 2001 to 10.6 per cent in 2015).

We also observe disproportionate increase in the mean earning of workers that belong to certain occupational or skill groups that possibly contribute to the rising inequality of earning. The mean salary of managers and technicians and associate professionals, for example, increased by 4.1 and 3.5 per cent annually, respectively. Moreover, for the period 2005–15, managers and technicians and associate professionals experienced the highest earning growth, whereas plant and machine operators only increased by 1.0 per cent annually. With this we may expect that inequality in earnings in the industrial sector or manufacturing may tend to increase.

Decomposing earning Gini into within/between occupational groups

In this section, we ask to what extent between- and within-occupation inequality contributes to inequality in earnings. As occupation category is typically ordered by skill level, between-occupation inequality tells us that the earning gap between high- and low-wage workers plays a big role. On the other hand, if within-occupation inequality contributes to a large part of the overall inequality, it can mean two things: (a) the gap between low- and high-wage workers is big in most occupation types; (b) occupation category does not necessarily reflect the monotonically increasing mean earning.

To answer the question, following Shorrocks (2013), we decompose the Gini coefficient of earnings inequality into within- and between-occupation inequality. It is more or less similar to the analysis done previously to decompose expenditure inequality into within and between sectors (agriculture and non-agriculture). More formally, we define y as individual earning and $G(y)$ as the Gini coefficient from distribution of y. Between-occupation inequality is defined as $G(y_b)$, where $y_b=(m_1, \ldots, m_j)$ is a vector in which the earning of individual workers y is replaced by the average earning in that occupation m_j. Within-occupation inequality is defined as $G(y_w)$, where $y_w=\left(y_1 \frac{m}{m_1}, \cdots, y_j \frac{m}{m_j}\right)$ is a vector in which earnings of all individuals are rescaled to ensure all occupations have average earning m. Using this approach, Gini coefficient G can be decomposed into between-occupation inequality G_B and within-occupation inequality G_W, or

$$G = G_B + G_w \tag{6}$$

where

$$G_B = \frac{1}{2}\big(G(y_b) + G - G(y_w)\big) \text{ and } G_W = \frac{1}{2}\big(G(y_w) + G - G(y_b)\big) \tag{7}$$

The result of the Shapley decomposition is reported in Table 8. First, generally, within-occupation inequality dominates in contributing to earnings inequality in Indonesia. Its contribution is between 65 and 70 per cent. At the beginning of 2001, between-occupation inequality only contributed to 35 per cent of overall earnings inequality. The share of the within-occupation component rose quite markedly from 65 per cent in 2001 to 70 per cent in 2015. Conversely, the share of the between-occupation component fell from 35 to 30 per cent during the same period.

Table 8: Gini index decomposed into inequality between and within occupations

	Actual				Shares constant				Means constant			
	2001	2005	2010	2015	2001	2005	2010	2015	2001	2005	2010	2015
1 Overall Gini	0.384	0.366	0.418	0.477	0.384	0.367	0.400	0.463	0.384	0.377	0.433	0.481
Shapley decomposition												
2 Between occupation	0.135	0.118	0.148	0.141	0.135	0.120	0.138	0.121	0.135	0.134	0.168	0.146
% Ratio	35	32	36	30	35	33	34	26	35	35	39	30
3 Within occupation	0.249	0.248	0.269	0.336	0.249	0.247	0.263	0.342	0.249	0.243	0.265	0.336
% Ratio	65	68	64	70	65	67	66	74	65	65	61	70

Source: authors' calculation.

From the counterfactual analysis of the Shapley decomposition, we find that the slowly increasing between-occupation inequality (4 per cent) is because of the widening gap of between-occupation earnings (37 per cent), not because of the changing composition of occupations. In fact, the composition has a narrowing effect so large that it almost negates the effect of the earning gap. This finding indicates that inequality in returns to occupation may play an important role in the rising overall earnings inequality, which will be discussed further analytically in a later section. (See also Table 9.)

Table 9: Concentration index

	Actual				Shares constant				Means constant			
	2001	2005	2010	2015	2001	2005	2010	2015	2001	2005	2010	2015
Gini between occupation	0.210	0.186	0.227	0.227	0.210	0.189	0.211	0.198	0.210	0.207	0.251	0.232
Concentration index												
RTI (country-specific)	0.171	0.140	0.177	0.168	0.171	0.147	0.151	0.152	0.171	0.164	0.211	0.193
% Ratio	81	75	78	74	81	78	72	77	81	79	84	83
RTI (O*NET)	0.145	0.119	0.137	0.140	0.145	0.123	0.124	0.125	0.145	0.143	0.185	0.169
% Ratio	69	64	60	62	69	65	59	63	69	69	74	73

Source: authors' calculation.

Testing job polarization

Job polarization refers to a decline in the share of medium-skilled jobs in total employment accompanied by an increase in the shares of high- and low-skilled jobs. Goos and Manning (2007) coined the term 'job polarization' when they showed that, in the United Kingdom over a 30-year period, occupations with the highest and lowest wages increased whereas middle-wage occupations had fallen. Autor et al. (2003) found similar results for the United States, Spitz-Oener (2006) for Germany, Adermon and Gustavsson (2015) for Sweden, and Green and Sand (2015) for Canada.

Despite numerous findings from developed countries, very few studies are available for developing economies and the findings are rather mixed. Maloney and Molina (2016) found no evidence of job polarization using census data for 21 developing countries, although they did identify 'incipient polarization' in a few countries, especially for Indonesia, Mexico, and Brazil. Fleisher et al. (2018) found a decline in middle-income skilled jobs and a rise in unskilled and self-employed jobs in

China; yet, they found no evidence of significant change in high-skilled jobs. In other studies, not directly related to job polarization, Kunst (2019) found that lost employment in developing countries during deindustrialization is mostly unskilled employment. An earlier study by Rodrik (2016) showed that the employment reduction is largely among low-skilled workers, while medium-skilled labour has changed little and high-skilled employment has increased in share.

To statistically test job polarization, we regress both the log change in employment share and the change in log mean wage of different types of occupation against the initial log (mean) wage (earning) and its square (Goos and Manning 2007; Sebastian 2018). This is done by estimating the following model:

$$\Delta \log E_{j,t} = \beta_0 + \beta_1 \log y_{j,t-1} + \beta_2 \left(\log y_{j,t-1}\right)^2 \tag{8}$$

where $\Delta \log E_{j,t}$ is the change in the log employment share of occupations between survey years t and t–1. Log $y_{j,t-1}$ is the logarithm of the mean labour earnings in occupation j in survey year t–1. (Log $y_{j,t-1}$)^2 is the square of the log means of initial labour earnings. Job polarization is identified if the quadratic shape of Equation (8) is statistically significant; that is, when coefficient β_1 is negative (and statistically significant) and coefficient β_2 is positive (and statistically significant). We also use a similar approach with the change in log earnings instead of employment as a dependent variable.

Job polarization is observed when the coefficient of initial mean wage is negative and statistically significant, and the coefficient of its square is positive and statistically significant. We used five different intervening periods: 2001–05, 2005–10, 2010–15, 2001–15, and 2005–15. The results of the regression are shown in Tables 10 and 11.

Table 10: Polarization regression in employment

	Log change in employment share				
Variables	2001–05	2005–10	2010–15	2001–15	2005–15
(Log) mean weekly wage (t–1)	7.930	–34.937**	–3.780	–16.435	–29.197**
	(4.810)	(16.039)	(7.213)	(12.802)	(12.104)
Square (log) mean weekly wage (t–1)	–0.307	1.381**	0.142	0.666	1.159**
	(0.189)	(0.634)	(0.279)	(0.506)	(0.476)
Constant	–51.151	220.647**	25.077	101.036	183.607**
	(30.595)	(101.370)	(46.602)	(80.957)	(76.819)
Observations	25	25	25	25	25
R-squared	0.220	0.134	0.025	0.131	0.143
Adjusted *R*-squared	0.149	0.0557	–0.0638	0.0516	0.0649
F-test	0.144	0.117	0.694	0.0708	0.0329

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

Source: authors' calculation.

Table 11: Polarization regression in earning

Variables	Change in (log) mean weekly wage				
	2001–05	2005–10	2010–15	2001–15	2005–15
(Log) mean weekly wage (*t*–1)	–2.498	–2.748	–7.203**	–6.452	–10.158**
	(1.890)	(4.231)	(3.430)	(5.894)	(4.385)
Square (log) mean weekly wage (*t*–1)	0.094	0.106	0.280**	0.245	0.395**
	(0.076)	(0.166)	(0.132)	(0.237)	(0.171)
Constant	16.525	17.825	46.357**	42.358	65.196**
	(11.800)	(26.861)	(22.234)	(36.677)	(28.033)
Observations	25	25	25	25	25
R-squared	0.308	0.028	0.099	0.248	0.185
Adjusted *R*-squared	0.245	–0.0609	0.0171	0.180	0.111
F-test	0.00303	0.690	0.0936	0.0181	0.0866

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

Source: authors' calculation.

We found an indication of job polarization during the period of 2005–10 and 2005–15. For those two intervening periods, we found that initial wage is negative and statistically significant, and its square is positive and statistically significant for the regression, with both the dependent variable change in employment share and change in earnings. All the coefficients are statistically significant at the 1 per cent level. This confirms the visual observation of the change in employment share of the skill deciles and skill quintiles (see Appendix A). Moreover, as a sign of polarization cannot be identified visually from the change in earning of the skill deciles and skill quintiles, the result of the regressions of change in earnings is interestingly new information strengthening the indication of job polarization in Indonesia, particularly during 2005–15, the period of rising overall inequality in Indonesia.

Testing routinization

Table 12 shows how RTI changes over time from 2001 to 2015. O*NET RTI clearly shows that the intensity of routine task declined from 0.40 in 2001 to 0.34 in 2015 for all workers. However, country-specific RTI shows that the decline only happened for paid employees.

Table 12: Average routine-task intensity (RTI) over time

RTI measure	All workers				Paid employees			
	2001	2005	2010	2015	2001	2005	2010	2015
Country-specific	0.80	0.81	0.88	0.87	0.73	0.71	0.70	0.70
O*NET	0.40	0.40	0.31	0.34	0.43	0.36	0.23	0.30

Source: authors' calculation.

Earlier analysis does not necessarily reflect the changing nature of work for lowering the intensity of routine jobs (routinization). We test this statistically by estimating the following model:

$$\Delta \log E_{j,t} = \beta_0 + \beta_1 RTI_{j,t-1} + \beta_2 \left(RTI_{j,t-1}\right)^2 \quad (9)$$

where $\Delta \log E_{j,t}$ is the change in the log employment share of occupations between survey years t and t–1. $RTI_{j,t-1}$ is the RTI measure in occupation j in survey year t–1. $(RTI_{j,t-1})^2$ is the square of the RTI measure in occupation j in survey year t–1. Job polarization is identified if the quadratic shape of Equation (9) is statistically significant, that is, when coefficient β_1 is negative (and statistically significant) and coefficient β_2 is positive (and statistically significant). The results of the regression are shown in Tables 13–16.

Table 13: Change in employment by O*NET RTI

	Log change in employment share				
	2001–05	2005–10	2010–15	2001–15	2005–15
O*NET RTI (*t*–1)	–0.068**	–0.177*	0.049	–0.242**	–0.190**
	(0.029)	(0.086)	(0.065)	(0.098)	(0.077)
Squared O*NET RTI (*t*–1)	0.030	–0.010	0.066	0.118	0.069
	(0.034)	(0.120)	(0.040)	(0.129)	(0.118)
Constant	–0.020	–0.098	–0.159*	–0.207	–0.171
	(0.066)	(0.166)	(0.077)	(0.145)	(0.136)
Observations	25	25	25	25	25
Adjusted *R*-squared	0.127	0.0566	0.0293	0.203	0.118

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

Source: authors' calculation.

Table 14: Change in earnings by O*NET RTI

	Change in (log) mean earnings				
	2001–05	2005–10	2010–15	2001–15	2005–15
O*NET RTI (*t*–1)	0.036***	0.052	–0.006	0.102**	0.063**
	(0.013)	(0.034)	(0.037)	(0.037)	(0.026)
Squared O*NET RTI (*t*–1)	–0.029*	–0.012	–0.022	–0.096***	–0.072***
	(0.014)	(0.035)	(0.022)	(0.033)	(0.022)
Constant	0.052*	0.029	0.035	0.134**	0.090***
	(0.028)	(0.034)	(0.023)	(0.051)	(0.027)
Observations	25	25	25	25	25
Adjusted *R*-squared	0.255	0.110	–0.0444	0.430	0.410

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

Source: authors' calculation.

Table 15: Change in employment by country-specific RTI

	Log change in employment share				
	2001–05	2005–10	2010–15	2001–15	2005–15
Country-specific RTI (*t*–1)	–0.092	–0.888**	–0.123	–1.152***	–1.026***
	(0.099)	(0.339)	(0.182)	(0.352)	(0.319)
Squared country-specific RTI (*t*–1)	0.016	0.846**	0.199	0.911**	0.859**
	(0.129)	(0.398)	(0.192)	(0.393)	(0.359)
Constant	0.042	–0.154	–0.125	–0.000	–0.044
	(0.043)	(0.162)	(0.126)	(0.103)	(0.102)
Observations	25	25	25	25	25
Adjusted *R*-squared	–0.0376	0.0682	–0.0492	0.162	0.152

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

Source: authors' calculation.

Table 16: Change in earnings by country-specific RTI

	Change in (log) mean earnings				
	2001–05	2005–10	2010–15	2001–15	2005–15
Country-specific RTI (*t*–1)	0.029	0.053	0.050	0.144	0.107
	(0.085)	(0.159)	(0.094)	(0.305)	(0.218)
Squared country-specific RTI (*t*–1)	0.053	0.039	–0.054	0.054	0.008
	(0.060)	(0.123)	(0.089)	(0.199)	(0.149)
Constant	–0.028	–0.034	0.011	–0.085	–0.059
	(0.042)	(0.068)	(0.060)	(0.137)	(0.098)
Observations	25	25	25	25	25
Adjusted *R*-squared	0.177	0.0330	–0.0786	0.154	0.0798

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

Source: authors' calculation.

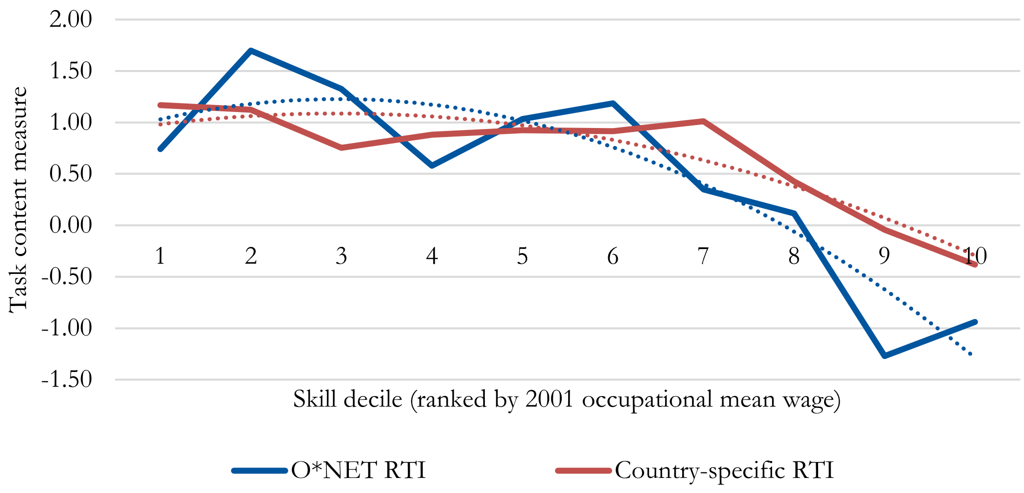
As previously discussed, we regress the changes in employment share with the initial routine intensity as well as using the changes in mean (log) earnings as the dependent variables. As can be seen from Table 13, the initial O*NET RTI is negative and statistically significant in all the regressions where the dependent variable is the change in (log) employment share for all periods except 2010–15. This negative relationship between the initial RTI and the change in employment share suggests that certain occupations that have an advantage in routine task at the beginning of each period will experience decline in the share of employment in a future period. The squared O*NET RTI is not significant, suggesting that the negative relationship does dies out. This is a sign of routinization.

However, when using country-specific RTI (Table 14), the square of the coefficient is positive and significant. It means that the negative relationship is U-shaped, or valid only until a certain point. For the long-term periods of 2005–15 and 2001–15, the RTI turning point is calculated as 0.632 and 0.702, respectively. The value is quite close to the mean of the RTI. In summary, using country-specific RTI (as developed by Lewadowski et al. 2019) gives rather mixed results in the Indonesian case. We also check whether change in earning is associated with RTI. The results are shown in Tables 15 and 16. We conclude there is no significant association between change in earning and RTI.

Looking at another regression, the relationship between initial O*NET RTI and changing employment suggests another quadratic relationship with an inverted U-shape (for at least the long-term periods 2001–15 and 2005–15). Initial RTI is positively associated with increasing employment until RTI of around 0.531, which is a bit higher than the mean. This suggests that during 2001–15 higher initial RTI is associated first with higher change in earning, yet at 0.531 the relationship is reversed. Using the country-specific RTI, we do not find any statistically significant relationship.

Despite the insignificant relationship between changing labour earning and RTI, we observed (see Figure 10) that RTI tends to be lower in a higher skill decile and higher in a lower skill decile. The relationship is more obvious if we use O*NET RTI but less obvious if we use country-specific RTI.

Figure 10: Routine-task intensity (RTI) across earnings decile



Source: authors' calculation.

6 Determinants of rising earnings inequality: the role of routinization

6.1 Methodology: reference influence function (RIF) decomposition

RIF regression is a method developed by Firpo et al. (2007, 2009) to estimate the effect of different variables at different points of the earning distribution. It is an extension of the Blinder–Oaxaca analysis that can only quantify the effect of different variables on the mean of the distribution (Blinder 1973; Oaxaca 1973).

RIF regression can be used as a decomposition that can quantify the extent to which changes in the Gini coefficient (inequality) over time can be attributed to changes in the distributions of worker characteristics and changes in the remuneration (returns) to these characteristics. In other words, utilizing the RIF regression, the change in Indonesia's inequality (Gini) can be explained by the composition effect (i.e. demographic, geographic characteristics, education level of workers, and work routine) and the effect of the earnings structure between occupations. Here, we can also include the index of RTI to determine the extent to which routinization contributes to the change in earnings inequality during the periods in question.

6.2 RIF decomposition results

We show two results of the RIF decomposition. The first result is based on the regression decompositions using country-specific RTI (Table 17), and the second result is based on the regression decompositions using O*NET RTI (Table 18).

As in the previous analysis, we divide the present analysis into five periods: 2001–05, 2005–10, 2010–15, 2001–15, and 2005–15. In all these periods, except the earliest (2001–05), we observed increase in earnings inequality. The largest change observed is from 2005 to 2015 when earning Gini changed by 0.111 point. For the whole period, 2001–15, earning Gini changed by 0.09 point. In all the periods where Gini of earning was rising, the changing earnings structure, not the composition of workers, contributed to the increase. For example, if we focus on the longer timespan, the changing earnings structure almost entirely (99.1 per cent) contributed to the 0.093-

point change in earnings inequality between 2005 and 2015. Moreover, when the period 2001–15 recorded higher increase in inequality (0.111), the contribution of composition effect is negative. The role of explaining the rising inequality is left to the changing earnings structure in the labour market. The supremacy of the earnings structure is generally similar in the proportion of its contribution throughout all the periods.

The decomposition effect plotted for each quintile can highlight the story more clearly. The plots for the periods 2005–15 and 2001–15 show the positively sloped curve of total change in log earnings, suggesting a notable rise in inequality. The changing composition component, however, is rather flat suggesting that it does not contribute much to the rising earnings inequality. The pattern of changing earnings structure across quantiles appears to follow quite closely the pattern of change in total earnings across quintiles. We then conclude that the returns to the endowment of labour must be behind the rising earnings inequality in Indonesia during the years 2001–15.

Table 17: RIF regression decompositions using country-specific RTI

	Country-specific RTI									
	2001–05		2005–10		2010–15		2001–15		2005–15	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Change	–0.018	(0.003)	0.052	(0.004)	0.059	(0.004)	0.093	(0.006)	0.111	(0.003)
Reweighting										
Composition	–0.003	(0.001)	0.013	(0.001)	0.001	(0.002)	0.012	(0.003)	0.017	(0.002)
Earnings structure	–0.015	(0.002)	0.038	(0.005)	0.059	(0.002)	0.081	(0.008)	0.094	(0.001)
RIF										
Composition	–0.002	(0.000)	0.018	(0.001)	0.003	(0.001)	0.029	(0.003)	0.025	(0.003)
Specification error	–0.002	(0.000)	–0.004	(0.000)	–0.002	(0.001)	–0.016	(0.001)	–0.008	(0.001)
Earnings structure	–0.015	(0.002)	0.038	(0.005)	0.059	(0.003)	0.080	(0.009)	0.095	(0.002)
Reweighting error	0.000	(0.000)	0.001	(0.000)	0.000	(0.000)	0.001	(0.001)	–0.001	(0.000)
Detailed structure										
Age	–0.012	(0.003)	0.002	(0.002)	0.003	(0.008)	–0.011	(0.004)	0.005	(0.001)
Sex	–0.001	(0.005)	0.000	(0.002)	–0.010	(0.002)	–0.006	(0.002)	–0.009	(0.000)
Education	–0.024	(0.016)	0.047	(0.016)	–0.004	(0.007)	0.029	(0.023)	0.050	(0.012)
Island	0.010	(0.015)	0.006	(0.009)	0.010	(0.002)	0.035	(0.017)	0.017	(0.001)
Sector	0.030	(0.004)	–0.019	(0.004)	0.012	(0.012)	0.022	(0.017)	–0.012	(0.000)
RTI	0.006	(0.012)	–0.057	(0.007)	0.026	(0.005)	–0.016	(0.002)	–0.032	(0.004)
Intercept	–0.023	(0.047)	0.059	(0.020)	0.021	(0.007)	0.028	(0.023)	0.077	(0.012)

Note: RIF, reference influence function; SE, standard errors; RTI, routine-task intensity.

Source: authors' calculation.

Table 18: RIF regression decompositions using O*NET RTI

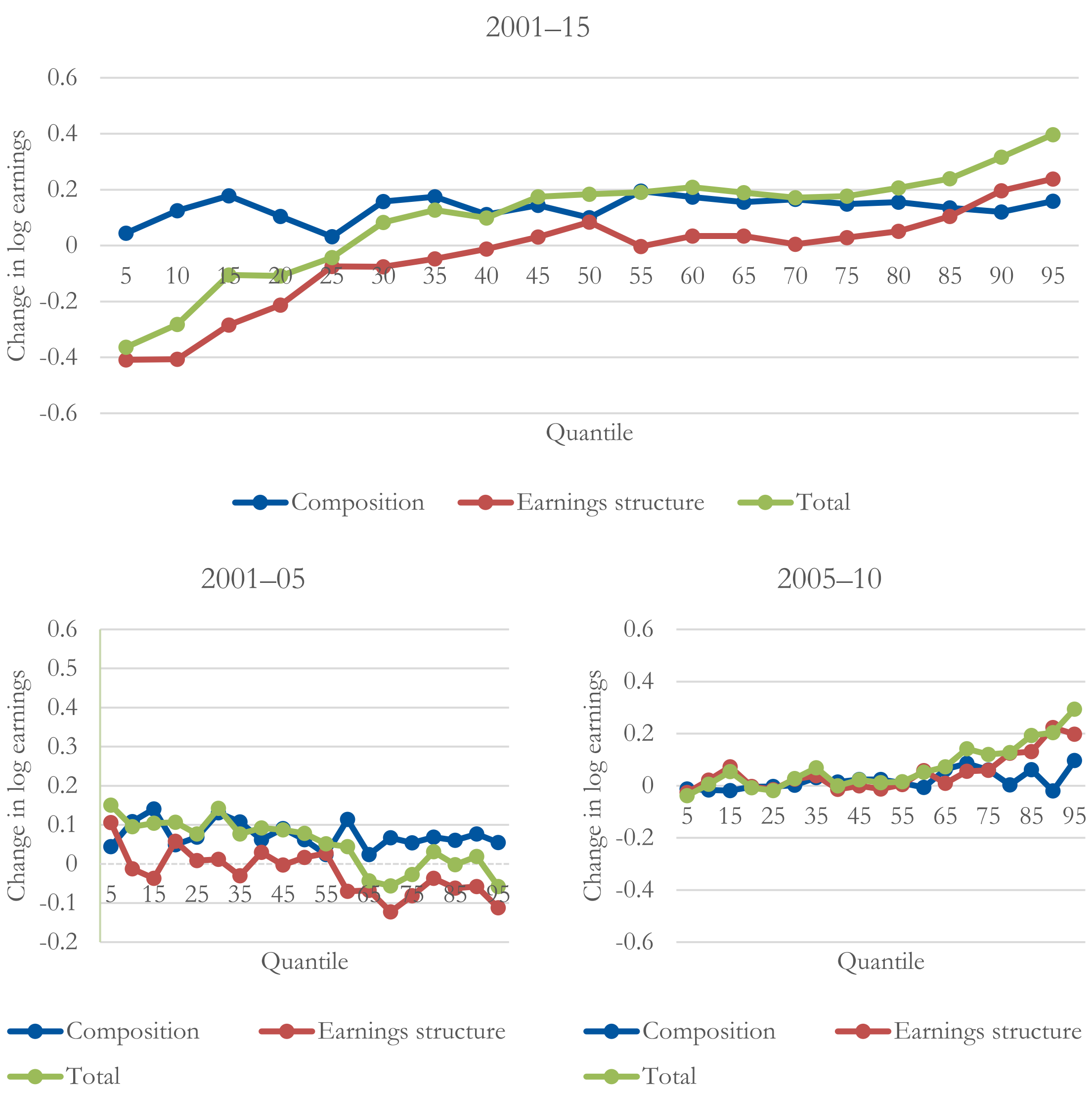
	O*NET RTI									
	2001–05		2005–10		2010–15		2001–15		2005–15	
	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE	Coefficient	SE
Change	–0.018	(0.001)	0.052	(0.002)	0.059	(0.000)	0.093	(0.001)	0.111	(0.001)
Reweighting										
Composition	–0.003	(0.004)	0.003	(0.000)	0.000	(0.000)	–0.001	(0.001)	0.003	(0.000)
Earnings structure	–0.015	(0.003)	0.049	(0.002)	0.059	(0.000)	0.094	(0.000)	0.108	(0.001)
RIF										
Composition	–0.001	(0.003)	0.006	(0.001)	0.003	(0.000)	0.016	(0.001)	0.011	(0.000)
Specification error	–0.002	(0.001)	–0.003	(0.001)	–0.003	(0.000)	–0.017	(0.001)	–0.008	(0.000)
Earnings structure	–0.015	(0.003)	0.049	(0.003)	0.060	(0.000)	0.094	(0.001)	0.108	(0.001)
Reweighting error	0.000	(0.000)	0.000	(0.000)	0.000	(0.000)	0.000	(0.001)	0.000	(0.000)
Detailed structure										
Age	–0.013	(0.008)	0.003	(0.002)	0.003	(0.001)	–0.010	(0.003)	0.004	(0.005)
Sex	0.000	(0.004)	–0.005	(0.001)	–0.011	(0.001)	–0.013	(0.002)	–0.014	(0.009)
Education	–0.017	(0.009)	0.051	(0.001)	–0.008	(0.016)	0.032	(0.009)	0.048	(0.003)
Island	0.010	(0.014)	0.009	(0.000)	0.012	(0.003)	0.034	(0.001)	0.022	(0.005)
Sector	0.036	(0.013)	–0.002	(0.003)	–0.008	(0.016)	0.024	(0.010)	–0.013	(0.003)
RTI	–0.008	(0.006)	0.000	(0.002)	0.020	(0.004)	0.009	(0.004)	0.015	(0.002)
Intercept	–0.023	(0.003)	–0.007	(0.000)	0.051	(0.008)	0.017	(0.006)	0.046	(0.009)

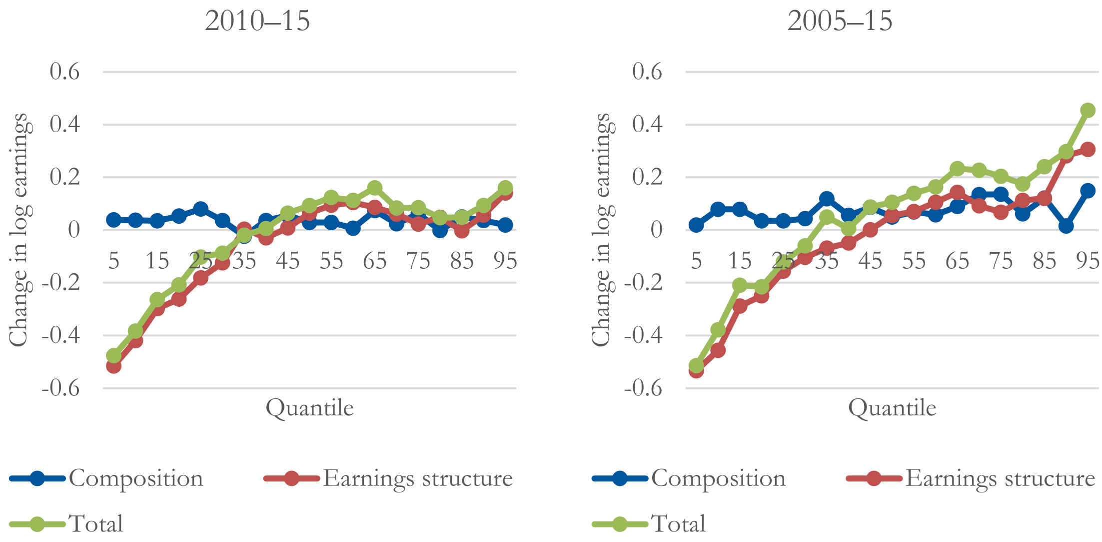
Note: RIF, reference influence function; RTI, routine-task intensity; SE, standard errors.

Source: authors' calculation.

A detailed composition of the change in Gini by quintile for earnings structure can help disentangle the effect of the changing earnings structure. Let us focus on the longer timespans (2001–15 and 2005–15). If we look closely at Figures 11 and 12, we can see that returns to education contributes significantly to the increase in earnings of workers belonging to the top 20 per cent, whereas returns to education contributes significantly to the decline in the earnings of the bottom 15 per cent. Education actually contributes the most to the changing earnings structure. For the years 2005–15 (Table 18), inequality changed by 0.111. The changing earnings structure contributes to a large part (0.108) of this change of 0.111 and the changing returns to education contribute 44 per cent (0.048) to the large part of 0.108. This is consistent with the earlier discussion about the returns to education, particularly the observation that the higher the education premium, the higher the level of education. For men, for example, the return to tertiary education (1.18) is more than twice the return to secondary education (0.48) in 2015. An earlier study by Akita and Miyata (2008) confirmed this finding. They considered urban–rural location and education as the main factors of expenditure inequality and examined inequality changes associated with urbanization and educational expansion in Indonesia. They found that the urban sector's higher educational group contributed significantly to overall inequality. This, together with educational expansion, led to a conspicuous rise in urban inequality. To mitigate overall inequality, the government needs to introduce policies that could reduce inequality among households with a tertiary education.

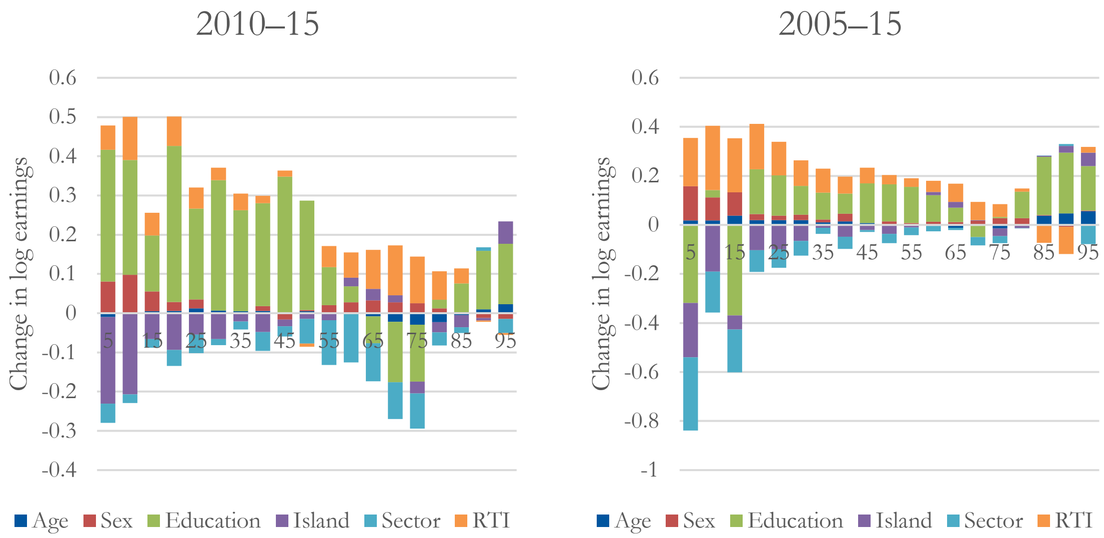
Figure 11: Decomposition of change in Gini by quantile (with country-specific RTI)





Source: authors' calculation.

Figure 12: Detailed RIF decomposition by quantile (with country-specific RTI)



Source: authors' calculation.

The other factor worth noting is the effect of geography (in this case, island of the workers' residency), which proves to be the second biggest factor after education (Table 18). This can indicate the regionally imbalanced nature of economic development during the periods in question. In other words, workers who reside in certain regions (e.g., Java island, the centre of economic activities in Indonesia) may be favoured for change in earnings relative to other regions, but the effect of demographic factors such as age and gender seem to be negligible.

The contribution of routinization (RTI) is mixed. It is not robust to the definition of the RTI we use. If we use RTI based on the O*NET database (Table 18), the changing returns to RTI is quite significant in explaining the changing earnings inequality (it is the third largest after education and geography).

7 Conclusions

Unlike the 1980s and 1990s, when Indonesia experienced a strong growth-enhancing structural transformation yet stable or declining inequality, after the AFC of 1997–98, Indonesia experienced a stalled industrialization accompanied by unprecedented rising inequality. The question on what exactly are the factors behind the rise in inequality during these periods remains unanswered. This paper explored the possibility of labour market dynamics including the changing nature of work contributing to rising inequality. Using various analyses with labour force survey data from 2001 to 2015, we highlight some important findings.

During 2001–15, earnings inequality (or more precisely, inequality of earnings for salaried workers) in general rose quite significantly. This is consistent with the trend of consumption inequality, Indonesia's headline indicator for inequality. This consistency leaves room for labour market dynamics as a possible explanatory factor for the rising inequality in Indonesia during the 2000s.

We observed a disproportionate increase in the returns to tertiary education. This naturally has a tendency towards increasing inequality. We also recorded an increasing share of workers with tertiary education. We found increasing shares of highly skilled as well as elementary workers, a sign of job polarization. However, we found that mainly within-occupation inequality, not between-occupation inequality, contributes to earnings inequality in Indonesia. More importantly, we found that between-occupation inequality of earning is mostly due to the widening gap of between-occupation earning, not because of the changing nature of occupation. This indicates that inequality in returns to occupation may play an important role in the rising overall earnings inequality.

We statistically tested the evidence of job polarization and found an indication of job polarization during 2005–10 and 2005–15. We also found that certain occupations that have an advantage in routine tasks (i.e. has higher RTI) at the beginning of a period experience decline in the share of employment in a future period. However, this result is not robust to different measurements of RTI.

Finally, using RIF regressions, we quantified the extent to which changes in the Gini coefficient (inequality) over time can be attributed to changes in the distributions of worker characteristics and changes in the remuneration (returns) to these characteristics. In all the periods where Gini of earning was rising, the changing earnings structure, not the composition of workers, contributed to most of the rise. The supremacy of the earnings structure is generally similar in the proportion of its contribution throughout all the periods. We conclude that the returns to the endowment of labour must be behind the rising earnings inequality in Indonesia during the years 2001–15. Furthermore, returns to education contributes significantly to the increase in earnings inequality. The contribution of returns to task content, however, is mixed. When O*NET RTI is used, the changing returns to RTI is quite significant in explaining the changing earnings inequality.

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Appendix A: Job polarization—visual inspection

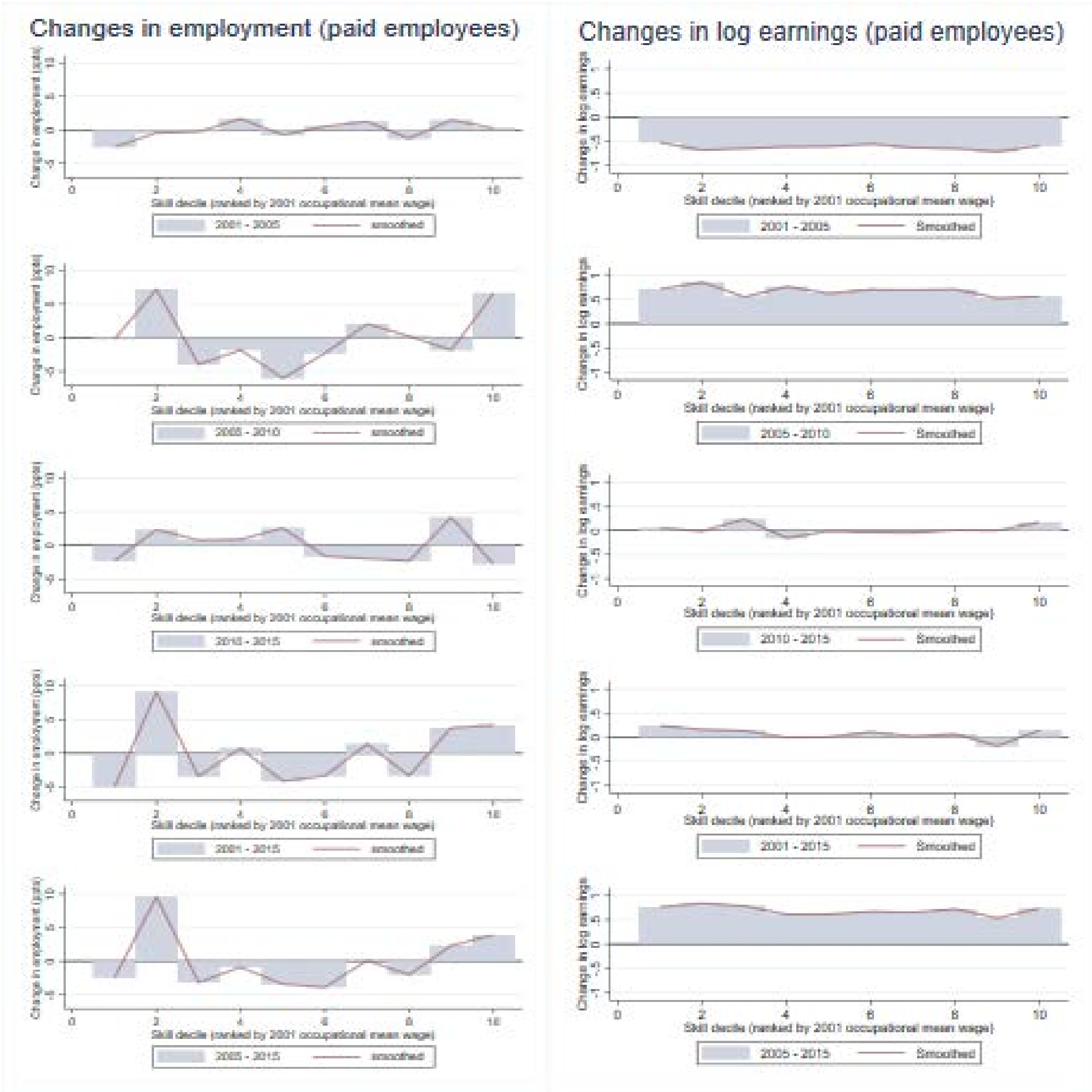
Appendix Figure A1 (left panel) shows the change in employment share (over different time periods) of paid employees, ranked by mean log earning of occupation types. The figure shows that over the period 2001–15, the share of workers in the category of labourers in mining, construction, manufacturing, and transport increases quite remarkably. The second largest increase is in the category of models, salespersons, and demonstrators. There is no clear pattern on whether the change in the share of workers' skill category is decreasing or increasing with the level of initial earnings. However, given the magnitude of the change in these two skill categories, it may indicate that the share of low-earning workers in the aggregate employment tends to increase over the period 2001–15. Appendix Figure A1 (right panel) shows the change in (log) earnings over different time periods. It shows no clear pattern for the relationship between the change in earnings by occupations.

Appendix Figure A2 shows the change in employment share (left panel) and log earnings (right panel) of paid employees (by skill decile), ranked by 2001 occupational mean wage (Autor and Dorn 2013). In the two different periods (of longer duration), namely, 2001–15 and 2005–15, there is a tendency that the shares of the lower decile (particularly decile 2) and the higher decile (particularly decile 10) increase, whereas the share of the middle decile decreases. We regrouped deciles into quintiles as shown in Appendix Figure A3. For the periods 2001–15 and 2005–15, a period of unprecedented rise in inequality in Indonesia as observed in many studies (e.g., see Yusuf et al. 2014), the shares of skill quintiles 1 and 5 rise, while the shares of skill quintiles 2, 3, and 4 fall. This is a sign of labour polarization. The right panels of Appendix Figures A2 and A3 show the change of earning, again ranked by initial years. There is no clear pattern that certain skill deciles or skill quintiles experience a growth of earnings significantly different from that of others.

Figure A1: Change in employment share and log earnings of paid employees, ranked by mean log earning

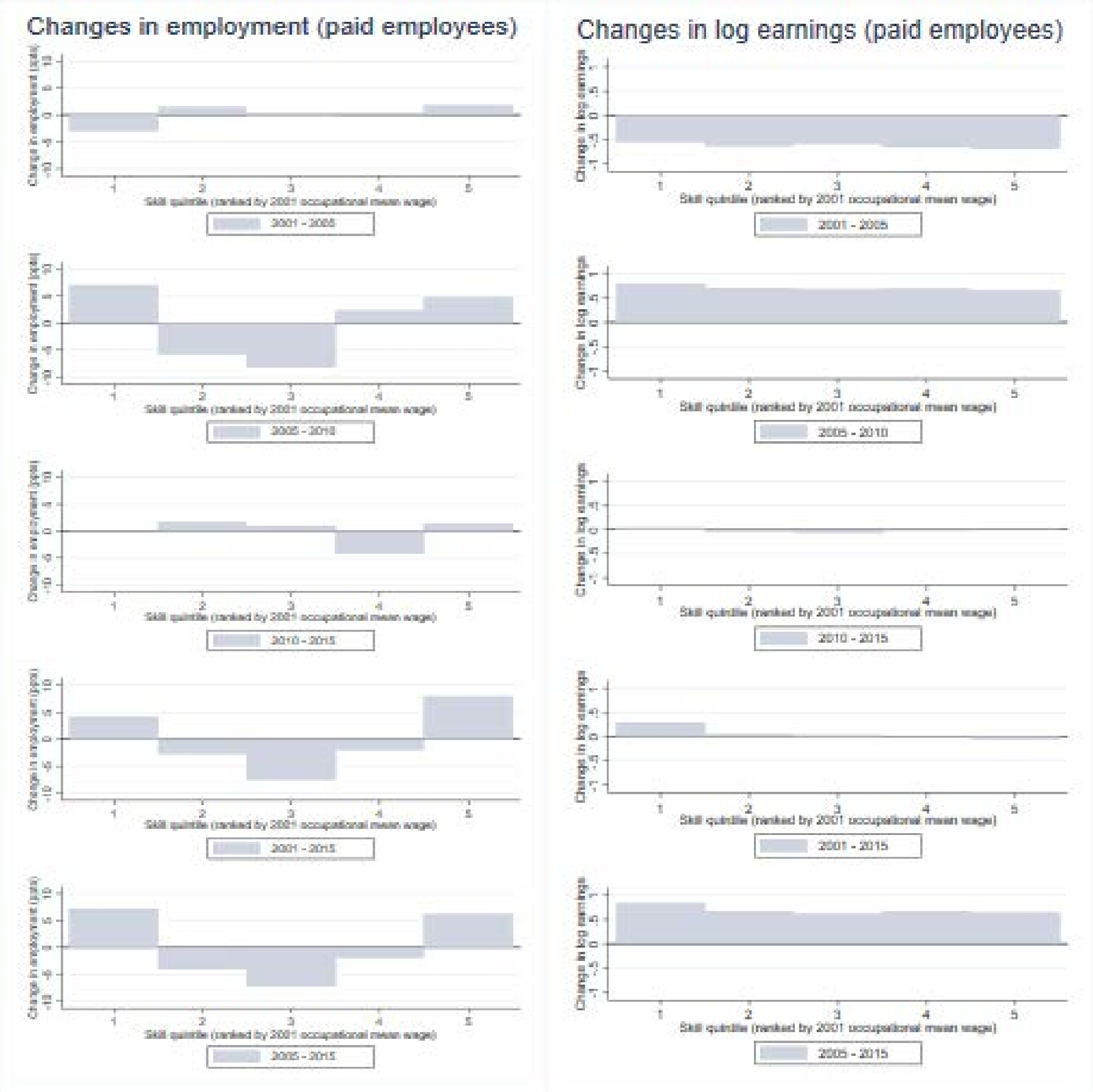
Source: authors' calculation.

Figure A2: Change in employment share and log earnings of paid employees (skill decile), ranked by 2001 occupational mean wage



Source: authors' calculation.

Figure A3: Change in employment share and log earnings of paid employees, skill quintile ranked by 2001 occupational mean wage



Source: authors' calculation.