

Testing for convergence clubs in real wage across Indonesian provinces from 2008 to 2020

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This study evaluates empirically the convergence in real wages across 34 Indonesian provinces. The authors apply the club convergence test on real wage data at the province level from 2008 to 2020. An overall convergence in real wages has not been found. Instead, three significant club convergences have been identified. Furthermore, regional factors that influence club convergence formation are investigated by using the ordered logit model. It has been found that club convergence formation is jointly influenced by the following factors: share of employment in the manufacturing sector, investment share to GDP, labour force participation rate, and the initial level of wage. The findings support the evidence of club convergence studies that emphasise the role of the initial condition and regional characteristics on the formation of club convergence. The results should alert national and provincial governments to synchronise policies promoting sound and competitive labour markets across provinces from a policy standpoint.

Keywords:
regional wage,
club convergence,
ordered logit model,
Indonesia

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Introduction

According to modern economic theories, people with indistinguishable talents will obtain equal remuneration in a wholly integrated labour market (Hicks 1963, Marshall 1920). Adhering to the same premise: many studies have tested for wage convergence in the context of broader labour market analysis, taking labour as a factor of production (Galizia 2015, Rosenbloom 1998, Rosenbloom–Sundstrom 2002). According to Dayanandan–Ralhan (2005), given the unrestricted mobility of people (in addition to lower transportation costs and the use of a common currency), testing

wage convergence as the price of labour within a country is more reasonable than across countries. While wage convergence is generally expected, the absence of convergence at the intra-national level implies the presence of regional imbalances, resource misallocation, and differences in the cost of living (González 2020).

In Indonesia, analysing wage convergence is relevant because it often becomes the main factor for many people to migrate. Based on theory, the economic reason is one aspect that could influence migration, and several approaches that underlie this among them were delivered by Mantra (1992) and Todaro–Smith (2003). Both agree that economic motives are reasons for migration, especially migration from rural to urban areas. The Indonesian Central Bureau of Statistics (BPS) recorded that the population in urban areas in 2020 is 56.7%, an increase from the 2010 figure of 49.8%. Furthermore, due to substantial urban expansion, which necessitates many workers, the figure is expected to rise to 66.6% by 2035. Another report from BPS shows that the number of lifetime migrants in Indonesia in 2019 is up to 29.8 million people, with migrant workers of 5.4 million people. Java island dominates the population of migrants in Indonesia, with approximately 51.2% of lifetime migrants and 56.5% of migrant workers residing in Java. The high number of migrants in Java is mainly influenced by wage conditions, living costs, and the availability of living facilities.

Improvements in people's mobility due to the rapid development of transportation infrastructure in Indonesia in the last decade add relevance to the study of regional wage convergence. For example, the number of airports in Indonesia increased from 148 in 2004 to 235 in 2018. Consequently, domestic passenger traffic increased dramatically during that period, rising from 34 million passengers per year in 2004 to 94 million passengers per year in 2018. Similarly, there has also been a rapid development in communication infrastructure due to the massive base transceiver station (BTS) constructed by Indonesia's telecommunication state-owned enterprise from approximately 26 thousand units in 2008 to 231 thousand units in 2020. This improvement in connectivity is expected to reduce disparity across Indonesian regions in many economic and social dimensions, including wages.

Against this backdrop, the present study focuses on convergence patterns of the long-run dynamics in wages across Indonesian provinces and the influencing factors of converging behaviour. Despite numerous studies on regional income convergence, less is known about regional wage convergence in Indonesia. Furthermore, this study uses the average net income per month of employees and labourers in 34 provinces from 2008 to 2020 as the primary indicator instead of the regional minimum wage (Upah Minimum Regional – UMR). In many cases, regional minimum wage is usually influenced by local government policy and other unconditional factors, so it does not optimally represent the real market situation. We also remove the effect of inflation on regional wages by converting the data from nominal to real terms.

We find three significant convergence clubs of regional wages by applying the club convergence technique (Phillips–Sul 2007). Interestingly, the composition of the

clubs using real wage is very similar to the one we obtained using nominal wage, implying the existence of a price-adjusted mechanism in regional wages. Provinces that converge into the higher wage clubs (Clubs 1 and 2) share similar characteristics: having a large proportion of manufacturing industries and high traffic of migrant workers, and locations of main national strategic infrastructure projects to promote investment. Our further analysis using an ordered logit model suggests that the formation of club convergence is significantly explained by the following variables: share of employment in the manufacturing sector, investment share to gross domestic product (GDP), labour force participation rate, and the wage level in the initial period. These findings also confirm the assumption of similar characteristics mentioned above.

The remainder of this paper is organised as follows. A brief review on wage convergence studies and the contribution of the present study section reviews the related literature, the Methods and data section discusses the methodologies and data. The results of club convergence identification and the influencing factors are presented in the Results and discussion section. Finally, the paper presents the conclusions.

A brief review on wage convergence studies and contribution of the present study

In labour market literature, wage convergence is generally evaluated from two perspectives: first, convergence in wages across workers and, second, across locations. Among others, the study of Fang–Yang (2011) is a well-appreciated work evaluating wage convergence across unskilled and skilled workers in China. Their results indicate that the wages of unskilled and skilled workers in China have converged, mainly due to the acceleration of structural change in the Chinese economy. Furthermore, the rapid growth in labour demand in China has exceeded the capacity of the labour market to supply, causing the wages of unskilled workers to escalate, known as the Lewis turning point.

However, studies investigating wage convergence across locations have gained popularity since the advancements in transportations and communication technologies increased labour mobility (Prado et al. 2020). The notion of free labour mobility across administrative borders is a necessary condition for the wage convergence mechanism to work. Regional wage differentials tend to decrease when there are no migration barriers, particularly from low-wage to high-wage regions (Collin et al. 2019).

A collection of studies shows evidence of regional wage convergence concerning flexible labour mobility. For example, using panel data covering 203 regions (Nomenclature of Territorial Units for Statistics or NUTS-2 level) in the EU from 1996 to 2006, Naz et al. (2017) find wage convergence only across internal regions

(regions within the same country) but no evidence of convergence for border regions (neighbouring regions across international borders). Using a similar approach, Enflo et al. (2014) apply panel fixed effect models and show that internal and external migrations contributed to wage convergence across Swedish counties before World War I, where internal migration occurred mainly during the interwar years.

As shown in other empirical studies, the mechanism of wage convergence across regions assumes a significant advancement in transportation and communications that can enlarge the scope of the labour market across geographical boundaries. With these theories and empirical backgrounds, it is natural to expect appealing findings from the analyses of regional wage convergence in Indonesia due to the development of transportation and communications infrastructure in the last decade.

The present study contributes to the existing literature by focusing on wage convergence analysis across regions that can be used to evaluate the degree of labour market integration in Indonesia. Previously, several studies examined convergence in Indonesia but mainly focused on variables related to income, such as GDP, GDP per capita, and total factor productivity (TFP). For example, applying the dynamic panel data approach, Firdaus–Yusop (2009) analyse convergence in income using province-level data of Indonesia. Applying the system generalized method of moments (GMM) estimation technique, they show convergence among Indonesian provinces during 1983–2003. However, the convergence speed is relatively slow (0.29%), much lower than the convergence speed observed in most regional convergence studies: 2% (Barro et al. 1991, Barro–Sala-i-Martin 1992). Using classical absolute and conditional convergence frameworks, Kharisma–Saleh (2013) analyse income convergence among 26 provinces in Indonesia during 1984–2008. They find a strong indication of absolute convergence and conditional convergence and refer to this evidence as the catching-up process, where provinces with lower income levels in 1984 tend to grow faster relative to the provinces with higher levels of income. Based on the system GMM estimation, they also find that the speed of convergence in Java is faster than that outside Java. The other study has been implemented by Vidyattama (2006) using a more extended dataset since the 1970s. Evidence from this study shows that significant changes in specific policies and economic development in Indonesia, including macroeconomic conditions and structural changes, affect the pattern of regional income convergence. Using the most recent data available, Aginta et al. (2020) analyse income convergence across 514 Indonesian districts from 2000 to 2017 using the club convergence framework. Their findings support the view of a lack of convergence in per capita income during the post-decentralisation era. Finally, Purwono et al. (2021) show that between 2011 and 2017, TFP convergence occurred in 33 Indonesian provinces, with intra-provincial exports having a greater impact on TFP convergence than international exports. Probably the closest study to ours is Aginta's (2021) analysis, which identifies club convergence in regional prices across provinces in Indonesia and further investigates the conditioning factors influencing

club convergence formation. Using consumer price index (CPI) data from 2012:01 to 2019:12 aggregated at the province level, this study shows the absence of overall convergence at the regional price level, and the dynamics of regional prices are characterised by four-club convergence. This extended research, which employs the ordered logit model, demonstrates that a one-unit change in labour productivity, inflation expectation, consumption growth, and spatial externalities considerably impacts the probability of provinces clustering into a different club.

We have shown that empirical research on wage convergence in Indonesia is scarce. The present article attempts to close the research gap by providing new evidence of regional wage convergence and its influencing factors.

Methods and data

Econometric methods: Testing for club convergence

Without the necessity of co-integration in time series, the log t -test developed by Phillips–Sul (2007) can investigate the existence of multiple convergence clubs (Bartkowska–Riedl 2012). In other words, although evidence of co-integration in time series is lacking, it does not automatically disprove convergence. With this advantage, many researchers have applied this method in various convergence analyses on different focuses, including income, productivity, financial development, and other socioeconomic indicators.

To identify the presence of club convergence on regional wage: this study applies Phillips–Sul’s (2007) modern test of club convergence. According to the model, we consider a panel data variable, for instance, y_{it} is expressed as:

$$y_{it} = \delta_{it} \mu_t \quad (1)$$

where i refers to individual units 1, 2, ..., N across time $t = 1, 2, \dots, T$, y_{it} is the dependent variable, δ_{it} indicates individual unit and time-specific components, or a time-varying idiosyncratic element. μ_t is not unit-specific and thus characterizes the common pattern of y_{it} . The dynamics of the idiosyncratic element, δ_{it} , can be expressed as:

$$\delta_{it} = \delta_i + \frac{\sigma_i \xi_{it}}{\log(t)t^\alpha} \quad (2)$$

where δ_i is a time-invariant individual-specific effect, and ξ_{it} is unnecessarily influenced by time, with a mean of 0 and variance of 1 across individual units. Departing from equation 2, the null hypothesis states that convergence exists if all individual units collectively approach the common transition path, such that:

$$\lim_{t \rightarrow \infty} \delta_{it} = \delta_i \text{ and } \alpha \geq 0 \quad (3)$$

Intuitively, the alternative hypothesis is $H_A: \delta_i \neq \delta$ for all i and $\alpha \geq 0$. To evaluate the convergence over the long-run time horizon, the relative transition parameter of an individual unit, h_{it} , is formulated as follows:

$$h_{it} = \frac{y_{it}}{\frac{1}{N} \sum_{i=1}^N y_{it}} = \frac{\delta_{it}}{\frac{1}{N} \sum_{i=1}^N \delta_{it}} \quad (4)$$

h_{it} represents the specific behaviour of individual unit i against the cross-sectional average. In the state of convergence under equation 3, $\delta_{it} \rightarrow \delta_i$, then $h_{it} \rightarrow 1$. This also implies that the cross-sectional variance of h_{it} converges to 0 ($H_t \rightarrow 0$),

$$H_t = \frac{1}{N} \sum_{i=1}^N (h_{it} - 1)^2 \rightarrow 0, \quad t \rightarrow \infty \quad (5)$$

where $H_t = \sigma_t^2$.

To empirically investigate the presence of convergence: the null hypothesis is tested with a log t regression model based on the variance ratio $\frac{H_1}{H_t}$:

$$\log\left(\frac{H_1}{H_t}\right) - 2 \log\{\log(t)\} = a + b \log(t) + \epsilon_t \quad (6)$$

for $t = [rT], [rT] + 1, \dots, T$ with $r \in (0,1)$

From the Monte Carlo simulation, Phillips–Sul (2007) argue that setting $r = 0.3$ is recommended. The null hypothesis is rejected when $t_b < -1.65$; if that is the case, the next step is to identify relative or club convergence.

Identifying club convergence and investigating conditioning factors of club convergence

The method of Phillips–Sul (2009) can identify whether different club convergences exist in the sub-sample in the absence of overall convergence in the full sample. Hence, after testing the overall convergence using log t regression, we use the clustering algorithm of Phillips–Sul (2009) for club convergence identification. A summary of this clustering algorithm is provided in Appendix 1.¹

The literature proposes an important discussion on the conditioning factors of club convergence from two different convergence perspectives. On the one hand, the club convergence hypothesis emphasises the importance of the initial condition for an economy's transition. On the other hand, conditional convergence argues that structural characteristics completely affect the long-run growth path, while the initial condition is exogenous (Von Lyncker–Thoennesen, 2017).

Although the club convergence method by Phillips–Sul (2007) clusters individual units according to their transition path estimates, it does not explain the factors that drive club formation as Azariadis–Drazen (1990) and Galor (1996) specify the club convergence hypothesis. To complete our analysis, we investigate the conditioning factors of club convergence formation. For this purpose, similar to Bartkowska–Riedl (2012), we apply the ordered logit model. Based on the theoretical considerations discussed previously, we test the initial condition and structural characteristics as explanatory factors in the estimation.

¹ See Phillips–Sul (2009) for further detailed discussion.

In practice, we denote each club convergence as $c = 1, 2, \dots, c$, where c is categorical according to the number of club convergence identified. Since the method of Phillips–Sul (2007, 2009) ranks the clubs according to the long-run trend of each individual in the respective club, we are allowed to arrange c as an ordinal variable. We assume that there is an unobserved variable y_t^* that is related to the long-run wage dynamics of provinces that force provinces to be clustered in a certain club. Thus, we can write the specification as

$$y_t^* = X_t \beta + \epsilon_t \quad (7)$$

where X_t is a vector consisting potential explanatory variables for club convergence membership, with $i = 1, \dots, 34$, indicating the province and ϵ_t have a logistic distribution. The model uses a maximum likelihood (ML) estimator to compute the probabilities of observing values of c . Note that although one can assess the directional effect of explanatory variables towards club membership with the sign of β coefficients, the magnitude does not contain any economic information. Therefore, in addition to the directional information given by the sign of β coefficients, we further compute the marginal effects of a given unit change in each explanatory variable on the predicted probability, holding other variables constant.

Data

As a proxy for regional wage, we use the average net nominal income per month received by a general worker (in thousand Indonesian rupiah [IDR]) published by the BPS. According to BPS, the net nominal income per month is defined as remuneration received during the last month in the form of money or goods by a person considered an own-account worker, a casual employee in agriculture, or a casual employee in the non-agriculture sector. The original wage data is in nominal terms, and its statistical measurement is uniform across provinces and consistent over time. Ideally, to reflect labour's purchasing power differential across provinces, the nominal wage should be deflated using each province's estimated absolute cost of living, similar to the approach used by Collin et al. (2019). However, due to data limitations at the province level, we could not estimate the absolute cost of living. Instead, we deflate the nominal wage using the provincial CPI of 2005 as the base year (2005=100).² In this way, we remove the nominal effects from the change in regional wage over time, but we acknowledge that our real wage data does not reflect regional variation in labour's purchasing power. Figure A1 in the Appendix 2 demonstrates the evolution of provincial real wages across time, and the summary statistics are provided in Table A1 in the Appendix 2.

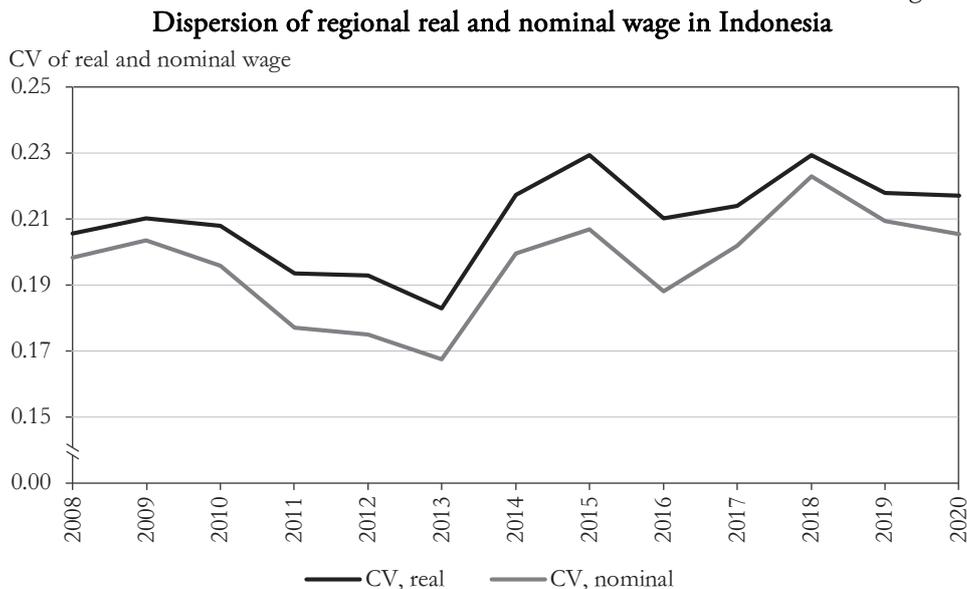
² Since the range of our observation is from January 2008 to December 2020, we intentionally select the year outside of our investigated interval as the base year to avoid using the same wage level (nominal equals real wage) at a particular year.

Results and discussion

Regional wage disparities across Indonesian provinces

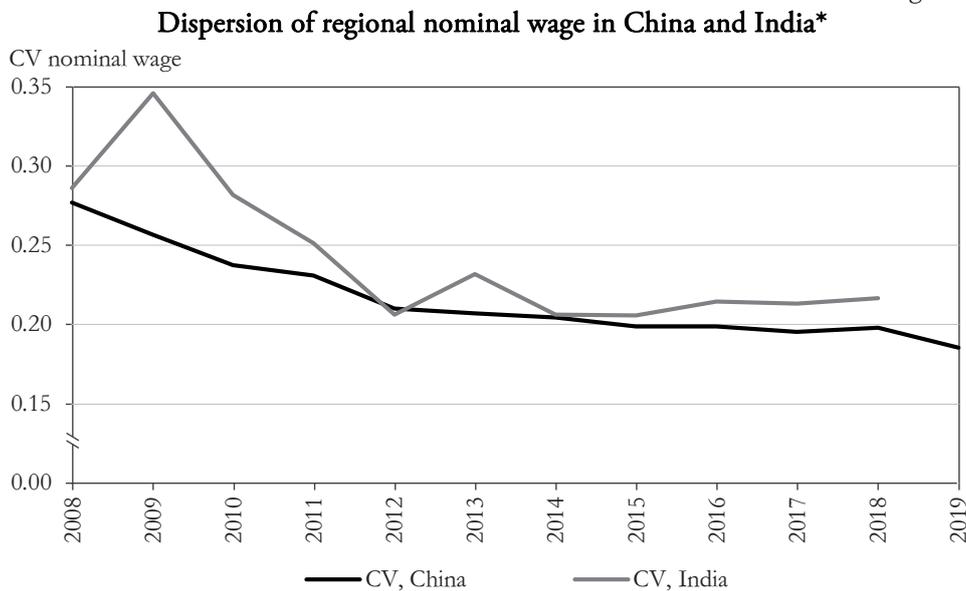
Before implementing the club convergence test, it is important to document the dynamics of wage disparity across provinces over time. Figure 1 plots the coefficient of variation (CV) of regional wages in real and nominal terms. The plot shows the absence of sigma convergence in both regional real and nominal wages; that is, the dispersion of wages in the final period is higher than in the initial period.³ Interestingly, the trend of regional wage dispersion in Indonesia is different from that in China and India. As shown in Figure 2, dispersion in regional wages in these two developing and most populated countries in Asia exhibits a declining trend during the same observation period. Although the difference in regional wage disparity at the end of the period is relatively subtle (0.185 in China, 0.205 in Indonesia, and 0.216 in India), the difference in the long-run trend is more recognisable, with regional wage disparity in Indonesia being more persistent than in China and India.

Figure 1



³ Derived from Barro–Sala-i-Martin (1992), sigma convergence refers to the decrease in the dispersion of the levels of a given variable across countries or regions over time.

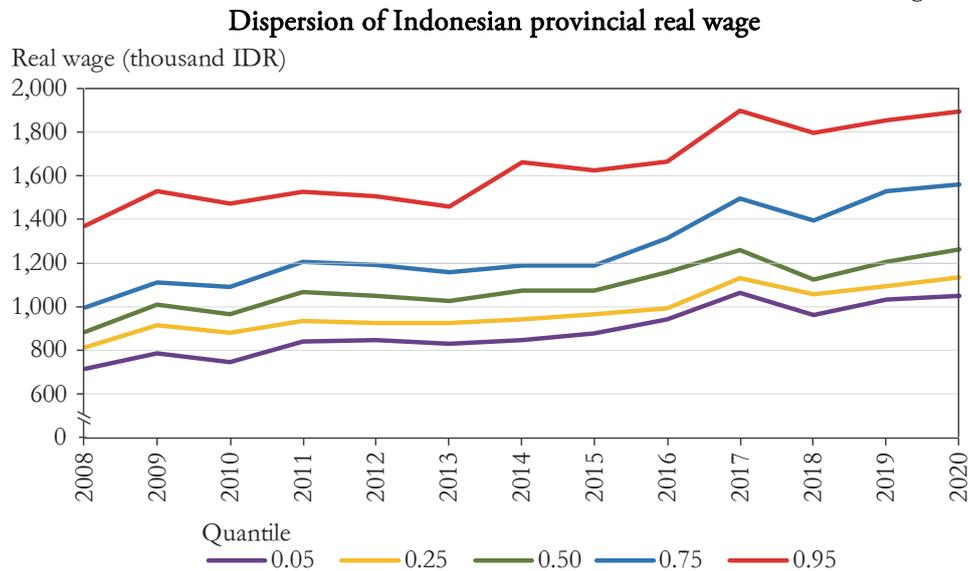
Figure 2



* CV for China and India is computed from 295 prefectural-level cities and 31 states and union territories, respectively. Regional wage data for China is available until 2018, while the data for India is available until 2019. Data for both countries are collected from CEIC.

We also illustrate the evolution of regional wage disparities among Indonesian provinces over the years. As seen in Figure 3, generally, the quantiles of the distribution show persistent gaps over time, indicating the tendency of steady regional wage disparities, similar to what is shown in Figure 1. Particularly, the persistent gap between quantile 95 and the rest of quantiles and the widening gap between quantiles 75 and 50 after 2017 implies a systematic difference between high-wage provinces and the rest of the provinces, which might be related to the structural differences. This dynamic of quantile distribution in provincial wage helps us understand that there is a strong symptom of lack of convergence in regional wage across Indonesian provinces despite the massive efforts from the government to enhance regional connectivity. However, the econometric method that we use in the present study makes it possible to identify club convergence, if any, albeit divergence in the entire sample. Therefore, in the next section, we will test the temporary conclusion of wage divergence with a formal econometric framework.

Figure 3



Testing and identifying for convergence clubs

We begin the formal test for convergence by applying log t regression on real wages across 34 Indonesian provinces over the 2008:01–2020:12 period. As reported in Table 1, the results suggest that the null hypothesis of overall convergence is rejected. Therefore, we can support our findings from preliminary inspection and conclude that Indonesian provinces do not converge to a common equilibrium in terms of real wages during the observation period. As real wage is partially linked to the price level in each province, this result is consistent with the evidence from previous studies where overall convergence is not observed in regional price dynamics across Indonesia prices (Jangam–Akram 2019, Aginta 2021). It is important to emphasise that, given the method used to build real wage data in this analysis as described, the absence of overall convergence from log t regression does not necessarily imply divergence in labour’s purchasing power among Indonesian provinces.

Table 1

Test of overall convergence			
	Coefficient	Standard error	t -statistics
Log(t)	-1.130	0.014	-79.721

Note: t -statistic < -1.65 implies the rejection of the null hypothesis of convergence.

We continue the analysis with the clustering algorithm by Phillips–Sul (2009) to identify club convergence. Table 2 presents the results.

Table 2

Club convergence test			
	Club 1	Club 2	Club 3
Coefficient	0.113	0.745	-0.014
Standard error	0.232	0.242	0.108
<i>t</i> -statistics	0.486	3.081	-0.126
Number of provinces	3	9	22

Note: *t*-statistic < -1.65 implies the rejection of the null hypothesis of convergence.

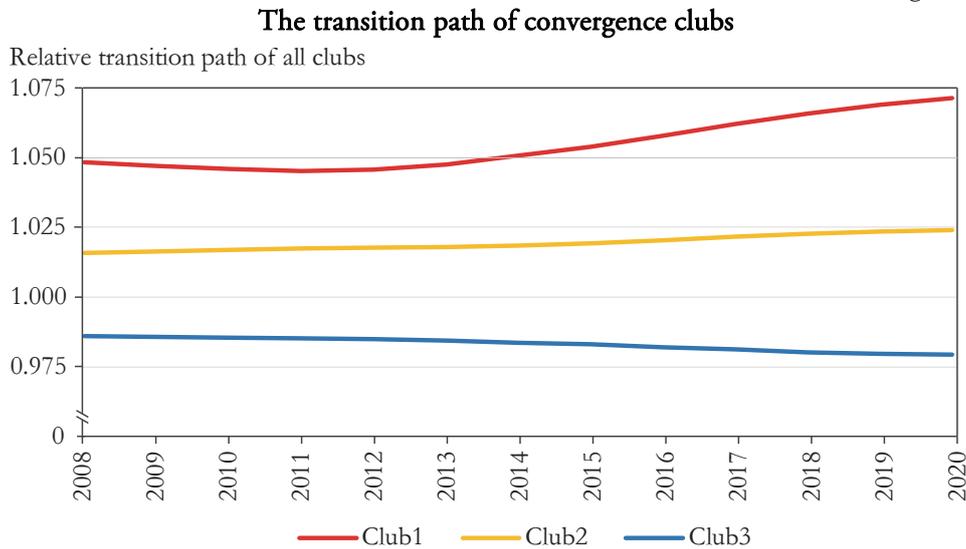
Club 1: Jakarta, Riau Islands, Banten. Club 2: Papua, East Kalimantan, North Kalimantan, West Java, West Papua, North Sulawesi, Bali, Central Kalimantan, South Sulawesi. Club 3: North Maluku, Riau, Maluku, West Sulawesi, South Kalimantan, Bangka Belitung, Southeast Sulawesi, West Sumatra, Aceh, Gorontalo, East Java, North Sumatra, Bengkulu, Yogyakarta, Central Java, South Sumatra, West Nusa Tenggara, Jambi, Lampung, Central Sulawesi, West Kalimantan, East Nusa Tenggara.

We find three significant initial clubs representing regional wages' convergence dynamics across Indonesian provinces.⁴ These results are similar to those Neagu (2020) reported for the Romanian case. Next, we use the merging method of Phillips–Sul (2009) described in Appendix 2 to test whether the initial clubs can merge with their adjacent club and thus generate higher club convergence. The results from the merging test suggest rejecting the convergence hypothesis in any merging pair ($\hat{b} < 0$ and *t*-statistics < -1.65).⁵ Hence, we confirm the initial three clubs as the final club convergence. The clubs are ordered from the highest to the lowest wage; club 1 consists of higher-wage provinces, while the lowest-wage provinces are clustered in club 3. As mentioned before, the club convergence method estimates the transition path of clubs and all individual units. Taking this advantage, in Figure 4, we show the evolution of the computed clubs' transition paths over time. Unlike using the absolute value of wages on the Y axes (similar to Figure 3), in Figure 4, we plot the relative transition path of each club to the cross-sectional average of all three clubs. Interestingly, there is an indication of gap reduction between clubs 1 and 2 from 2008 until 2012. However, the transition path of club 1 exhibited an increasing trend with a significantly higher slope than that of club 2, resulting in a larger gap between the two clubs. In other words, the pattern of expanding differences among the clubs' transition paths supports the identification of significant club convergence over overall convergence. Instead of forming a converging shape, reflected in smaller gaps between clubs over time, the three transition paths demonstrate increasing dispersion between clubs, where club 1 is systematically above the average, club 2 steadily moves from below towards the average, while club 3 is consistently below the average.

⁴ The evaluation of club convergence is executed using the club convergence package in R developed by Sicheira–Pizzuto (2019).

⁵ We also implement the merging procedure according to Von Lyncker–Thoennessen (2017). The test gives identical results from the merging test of Phillips–Sul (2009).

Figure 4



We then analyse the within-club transition dynamics by plotting the transition path of provinces in each club, as shown in Figure 5. Unlike the diverging pattern shown in Figure 4, the transition paths in Figures 5 (a), (b), and (c) demonstrate a clear convergence pattern, with a smaller gap between provinces in the final period. In club 1, although real wages in Banten and Jakarta improve over time, the convergence is largely driven by the declining real wage in the Riau Islands, particularly since 2015. It is worth noting that the Riau Islands is renowned as the country's industrial hub, with shipbuilding, oil and gas, and electronics manufacturing among its mainstays. Despite its proximity to Singapore, the performance of the islands' industrial sector has deteriorated, with diminishing levels of foreign direct investment (FDI) and exports (Negara–Hutchinson, 2020). Meanwhile, Jakarta is the country's capital city where large business and financial services are centred, and Banten is a province that shares a border with Jakarta and relies heavily on the manufacturing industry to support its economy (approximately 37% of GDP).

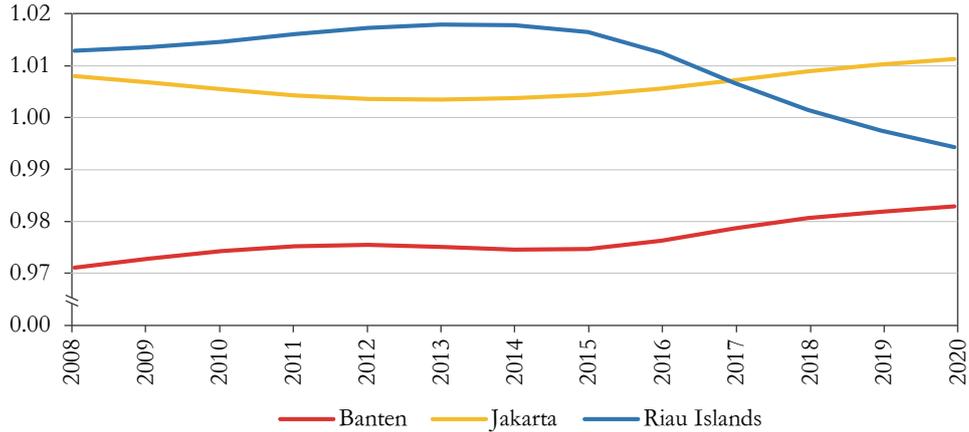
The convergence in club 2 is due to a combination of real wage decline in mining-based provinces (e.g., East Kalimantan, Papua, and West Papua) and improved conditions in the industrialised province of West Java and the newly established province of North Kalimantan. Similarly, the consistent growth of real wages in Java's other two industrialised provinces (Central Java and East Java, with manufacturing shares of 30% and 34% of GDP, respectively) dominates the club 3 convergence process. Conversely, the wage condition in East Nusa Tenggara continues to decline. Agriculture's prolonged dominance – most of which is low-tech and subsistence-oriented, plays a significant role in this phenomenon (ILO 2013).

Figure 5

The transition path of Indonesian provinces within each convergence club

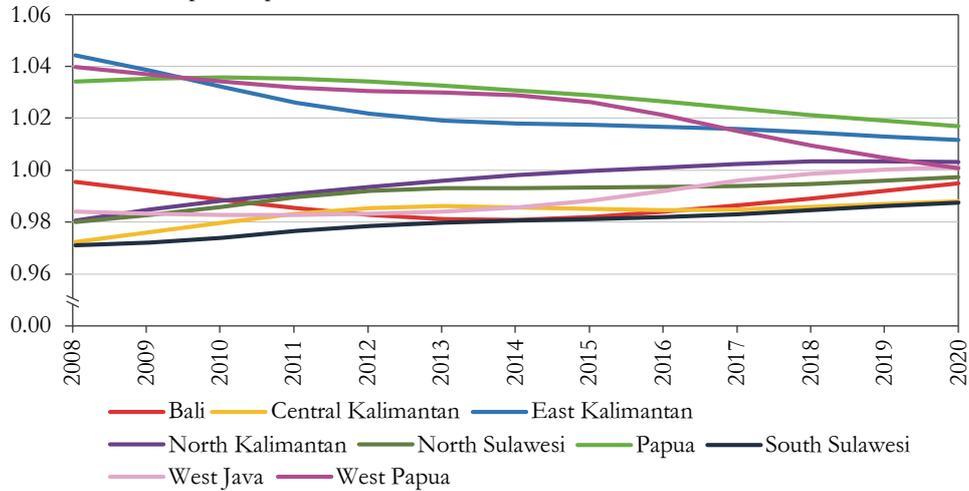
a) Club1

Relative transition path of provinivies in Club1

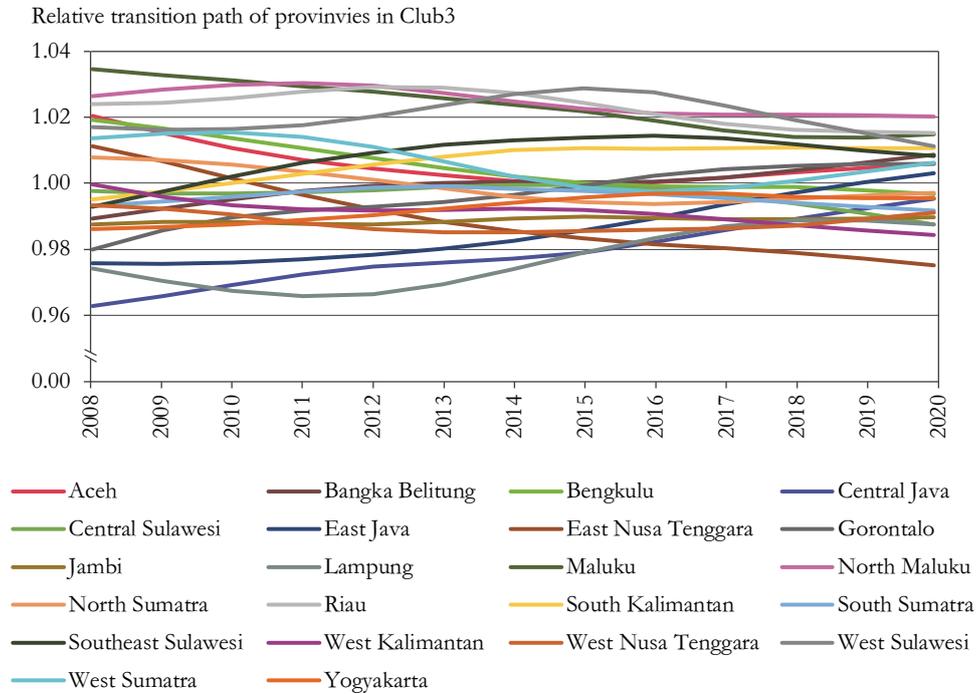


b) Club2

Relative transition path of provinivies in Club2

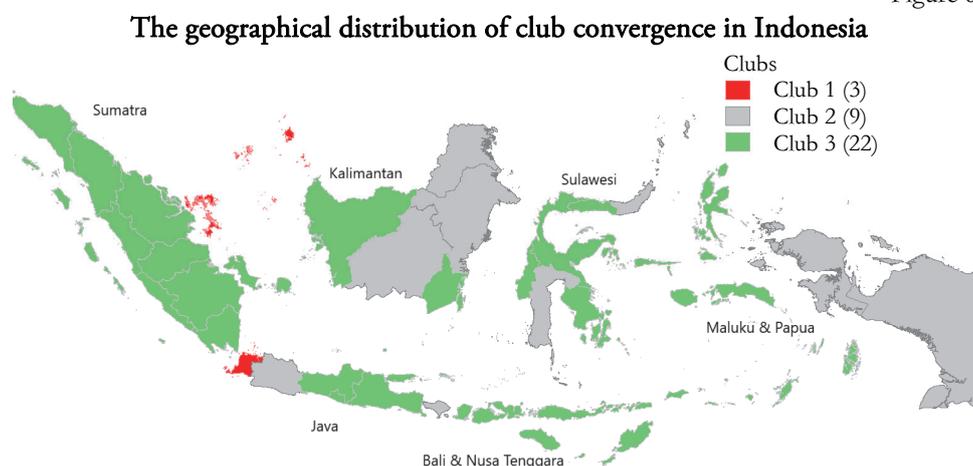


c) Club3



Finally, we visualised the geographical distribution of club convergence in Figure 6. It is worth noting that we capture geographical effects of club convergence (Barro et al. 1991, Quah 1996), similar to what has been documented in the study of Aginta et al. (2020) and Aginta (2021) when studying regional income and price convergence in Indonesia. These geographical effects are apparent on Sumatra Island, where a province and its neighbouring provinces are clustered in the same club (club 3). A similar pattern is also observed in the distribution of club 2 (in Kalimantan and Papua islands) and club 1 (where Jakarta and its neighbour Banten clustered together).

Figure 6



The club convergence test results show the presence of a persistent gap in regional real wages across Indonesian provinces. The results also reflect wage rigidity and heterogeneity in macroeconomic and labour market conditions across provinces. However, to date, we do not know which components of macroeconomic and labour market conditions explain regional wage disparity across Indonesian provinces. Therefore, in the following section, we investigate the important factors contributing to persistent regional wage disparity. More specifically, we aim to provide empirical evidence to address the following question: what regional factors influence the formation of club convergence?

Factors influencing the club convergence

This section examines and discusses the important conditioning factors that theoretically influence club convergence formation. The club convergence hypothesis places a considerable weight on the crucial roles of the initial condition and structural characteristics in influencing the convergence process; that is, countries or regions will only converge to a common steady state if they depart from similar initial conditions and share the same structural characteristics (Galor 1996).⁶ Therefore, in addition to the level of real wage in 2008 to control for the initial condition, we also include sectoral and labour market indicators to capture the role of structural characteristics in club convergence formation. To be consistent with the theoretical

⁶ In the context of the neo-classical framework, multiple steady-state equilibria could arise from the variation in factor endowments. In a particular case, the initial level of capital-labour ratio can be used as a proxy of factor endowments that determine the shape of the steady-state path of an economy. Meanwhile, economies that use similar production technology tend to evolve toward a common steady state. See Galor (1996) for a more in-depth look at the theoretical models behind convergence clubs.

foundation of the convergence framework, the selection of variables in our ordered logit model is also comparable with previous club convergence studies (Bartkowska–Riedl 2012, Cutrini 2019, Von Lyncker–Thoennesen 2017).

The ordered logit specification requires variables to be explained in an ordinal manner (McKelvey–Zavoina 1975). Hence, we re-arrange the clubs by using the wage level of each club as a reference to order the clubs from 1, 2, and 3 as high-, middle-, and low-wage clubs, respectively. Finally, as in the previous literature, we use these ordered clubs as the dependent variable of the regression, while independent variables consist of the main factors that theoretically influence club convergence. Table 3 contains the definitions and sources of the variables.

Table 3

Variables in ordered logit estimation

Variable	Definition	Source
Initial value of wage (2008)	Real wage in 2008 (in thousand IDR)	BPS
Manufacture employment share	$\frac{\text{Number of people employed in manufacturing sector}}{\text{Total number of people employed}}$	BPS
Investment share to GDP	$\frac{\text{Total investment}}{\text{Total GDP}}$	BPS
Labour force participation rate	$\frac{\text{Number of persons in the labor force}}{\text{Population aged ten (10) years and over}}$	BPS
GDP	Real GDP (2010 = 100) in log form	BPS

We report the marginal effects on the probabilities computed from the ordered logit model in Table 4.⁷ The individual marginal effect measures how much the probability of a province being included as a member of a specific club changes with respect to a small change in the explanatory variables. In this way, our results can explain how a unit change in the independent variable affects the probability of provinces clustered into club 2 (middle-wage) and club 3 (low-wage). However, our model cannot precisely compute the marginal effects on the probability of club 1 (high-wage). We consider this to be the problem of insufficient samples in club 1 (high-wage).⁸ Nonetheless, the model clarifies how the selected factors influence the membership of the convergence club.

⁷ See Long–Long (1997) for a discussion on interpreting the results of ordered logit models.

⁸ Aginta (2021) and Bartkowska–Riedl (2012) also encounter a similar problem in their respective studies.

Table 4

The results from ordered logit estimation

Variables	Marginal effects on probabilities		
	Club 1 (high)	Club 2 (middle)	Club 3 (low)
Initial value of wage (2008)	0.000 (0.000)	0.009** (0.004)	-0.009** (0.004)
Manufacture employment share	0.000 (0.000)	0.189** (0.106)	-0.189** (0.106)
Investment share to GDP	0.000 (0.000)	0.162** (0.078)	-0.162** (0.078)
Labour force participation rate	-0.000 (0.000)	-0.046** (0.022)	0.046** (0.022)
GDP (<i>in logs</i>)	0.000 (0.000)	0.242 (0.211)	-0.242 (0.211)
Number of provinces	3	9	22

Note: Numbers in parentheses are standard errors. ***, **, * show significant level at 1, 5, and 10%, respectively.

All the ordered logit coefficients show the expected signs. Additionally, the magnitude of the coefficients deserves special attention. Our results point to the significance of structural characteristics in explaining club convergence formation.⁹ Specifically, the share of employment in the manufacturing sector is the most important structural element driving club convergence. A one-point increment in the manufacturing employment ratio would significantly raise the probability of a province converging to the middle-wage club (club 2) by 18% while reducing the likelihood of a province converging to the low-wage club (club 3). In this respect, our findings appreciate the conventional view that claims labour productivity is generally higher – therefore, higher wages – in the manufacturing sector. The investment share in GDP and labour force participation rate is the other important structural determinant, to a lesser extent than the share of employment in the manufacturing sector, but has a larger effect than the initial level of real wage in 2008. Overall, our results imply that the mechanism of club convergence formation in real wages across Indonesian provinces mainly works through underlying attributes in regional labour market conditions. Next, we elaborate on the effects of each factor in detail.

The manufacturing employment share has a positive effect for clubs 1 and 2, whereas it shows an adverse effect for club 3, which means that the province with a higher manufacturing employment share has a higher wage than the rest. This result is also consistent with Felipe et al. (2019) finding, in which high-tech manufacturing firms generally pay higher wages in Indonesia. Furthermore, they also reveal that differences are likely due in part to differences in the skill requirements of the manufacturing sector, with average levels of education and training being significantly

⁹ Cutrini (2019) empirically finds comparable results on the relative importance of structural variables than the initial level of income per capita in influencing club membership across 274 European regions on a NUTS-2 level.

higher. Moreover, the high productivity rate in the manufacturing sector often becomes the main reason labour in the manufacturing sector often earns a higher wage than labour in other sectors. Strain (2019) finds evidence of a strong link between productivity and wages. In detail, he describes that when properly measured, productivity and compensation show very similar trends in the last few decades.

Similar to the share of manufacturing employment, the investment-to-GDP ratio also demonstrates a positive effect on higher wage clubs. This result is also similar to the finding of Baskoro et al. (2019), who conclude that the relatively higher wage in FDI companies is possibly explained by the higher productivity of labour, which represents an improvement of labour skill and in line with the shift in Indonesian industrial character. Lipsey–Sjoholm (2001) highlight the higher level of workers' education in foreign-owned firms as the main factor explaining why foreign-owned firms in Indonesia might pay a high price for labour. Another reason is that foreign-owned firms wish to reduce employee turnover to secure their technological advantages from being copied by their competitors. The significance of investment in affecting regional wage also implies a regional imbalance in economic development, where investment activities are largely concentrated in a few provinces with better infrastructure, strategic geographical position, and natural resource endowment. For example, provinces like Jakarta, Banten, and Riau islands are in club 1 and have better infrastructures than other provinces. These provinces also have strategic geographical locations surrounded by well-managed transportation infrastructure, and thus will induce higher labour and capital mobility.

Meanwhile, the labour force participation rate shows a different effect in which the sign of the coefficient is negative in clubs 1 and 2, whereas it is positive in club 3. This means that a higher labour force participation rate decreases the probability of being in higher wage clubs, reflecting the standard labour supply and demand conditions. A higher labour supply relative to its demand leads to downside pressure on wages. Similar to what is mentioned by Herr (2002), we find evidence of a negative relationship between wages and labour supply.

The initial wage level shows a positive effect for clubs 1 and 2, which means that the probability of the province belonging to clubs 1 and 2 is higher when the province has a higher initial wage level. Inversely, the adverse effect for club 3 means that the province with a higher initial value of wage has a small probability of belonging to club 3. The effect of the initial condition in our study is also in line with Bartkowska–Riedl (2012) findings, which shows that the region's initial state plays a crucial role in the European areas to determine which club they will belong.

As for the last variable, although statistically insignificant, the size of the economy, or GDP, shows a positive effect on higher-level wage clubs. This implies that the cross-sectional variation in regional wages in Indonesia is less connected to the size of the economy. Instead, regional economic and labour market structures are the main factors shaping the level of regional wages.

Conclusions

This study empirically investigates the convergence of regional wages in Indonesia, a large and geographically diverse developing country. Specifically, we address two crucial questions in the empirical analysis. First, can we identify club convergence in regional wages in Indonesia, despite the presence of prolonged wage disparity? Second, to what extent do region-specific characteristics influence club convergence? To achieve these goals, we divide our strategy into two main steps. First, we test whether regional wages converge to a common steady-state using log t regression developed by Phillips–Sul (2007, 2009). In the absence of overall convergence, we further check for the presence of club convergence. Second, we investigate the essential factors that influence club convergence formation.

Our results from the first step show three significant clubs representing the convergence dynamics of regional wage across Indonesian provinces: three provinces clustered in club 1, nine provinces in club 2, and 22 provinces in club 3. Overall, the results from our initial investigation imply that, based on the long-run dynamics of regional real wages from 2008 to 2020, Indonesian provinces can be clustered into three club convergences. The presence of club convergence from our results is similar to the finding of Neagu (2020) in the context of regional wage analysis in Romania.

In the second part, the results from the ordered logit model show that regional characteristics related to labour market conditions largely explain the formation of club convergence in provincial wages. Variables such as manufacturing employment share, investment-to-GDP ratio, labour force participation, and the initial condition of wage significantly influence the convergence club formation, while the size of the economy, or GDP, exhibit insignificant effects. Our findings are compatible with the theoretical underpinnings of the convergence concept and comparable to previous club convergence investigations (Bartkowska–Riedl 2012, Cutrini 2019, Von Lyncker–Thoennesen 2017).

Taken together: our results suggest four key points concerning policy implications for reducing wage disparity across Indonesian provinces. First, it is imperative to promote the development of manufacturing industries in all provinces. Manufacturing sectors would attract skilled workers from different places and bring positive technical spillovers to local workers. In turn, this would create a trickle-down effect that tends to help reduce wage disparity, as in the case of India (Jain, 2018). Second, boosting investment is equally important, not to mention attracting inward FDI. Technology spillovers and demand creation effects brought by FDI firms would positively influence the productivity of local firms and workers, leading to improved wage levels. Third, reducing wage differentials across regions requires convergence in education. Therefore, improving education quality in less developed regions should become a priority and promote industrialisation and investment to guarantee the provision of educated labour and skilled workers. Finally, the Indonesian government

needs, both national and local, to continue enhancing healthy competition in the regional labour market to promote efficiency in resource allocation across regions.

However, one limitation of this study is the relatively short observation timeframe used to study wage convergence. This may impact the estimation of club convergence, as the power of the log t -test decreases as the time dimension shortens (Phillips–Sul 2007, 2009, Von Lyncker–Thoennesen 2017). Furthermore, based on the geographical distribution of the clubs, one is tempted to conclude that real wages in Sumatra Island converge perfectly to club 3, except for the Riau Islands. This might not be the case when the spatial unit used is at the district level, as observed in the context of regional income convergence in Indonesia (Santos-Marquez et al. 2021). Hence, future studies could investigate regional wage convergence across Indonesia's district level, subject to data availability. Such studies would allow us to look more deeply at the role of spatial dependence within a province and between adjacent districts belonging to different provinces in shaping regional wage. Finally, depending on data availability, future studies could examine regional wage convergence in Indonesia by utilising real wage data that capture cross-sectional differentials in labour's purchasing power.

Appendices

Appendix 1: Clustering algorithm for club convergence

When the results from log t -test regression reject the null hypothesis of overall convergence, the application of the clustering algorithm introduced by Phillips–Sul (2009) can be applied for club convergence identification. The following steps briefly summarize the mechanism of the algorithm:

Step 1: Ordering based on final observation

All individual units (in our study, provinces) are arranged in descending order based on their last observation in the time-series dimension of the panel.

Step 2: The formation of the core group

Apply log t regression to the first k individual units (provinces), where $2 \leq k < N$. The core group is established when the $t_b > -1.65$. If the t_b in the first k unit < -1.65 , the first unit is dropped, and the log t regression is applied for the second and third units. This step continues until the condition where t_b of the pair units > -1.65 . In the case where no pairs of units showing $t_b > -1.65$ in the entire sample, the conclusion is that there are no convergence clubs in the panel.

Step 3: Filter the data for club membership

When the core group of a club is successfully identified, the remaining individual units (provinces) that do not belong to the core group will be added one at a time and evaluated using log t regression. If the inclusion of an additional unit results in $t_b < -1.65$, then the club convergence only has the core group. Otherwise, a new group is formed when $t_b > -1.65$.

Step 4: Repetition and stopping rule

Apply log t regression to the remaining individual units (provinces). If the results suggest rejecting the null hypothesis of convergence, repeat steps 1 to 3. If there is no core group identified for which $t_b > -1.65$, label the remaining individual units (provinces) as divergent and the algorithm stops.

Appendix 2: Brief description of the club merging procedure

Apply log t regression to the first two adjacent groups identified by the initial clustering mechanism. If $t_b > -1.65$, a new club convergence is formed from these two groups. Next, repeat the step by adding the next group one at a time until the condition of $t_b > -1.65$ holds. If the null of convergence is rejected, we conclude that all previous groups converge, except for the last added one. Restart the merging algorithm from the club where the convergence hypothesis does not hold.

Table A1

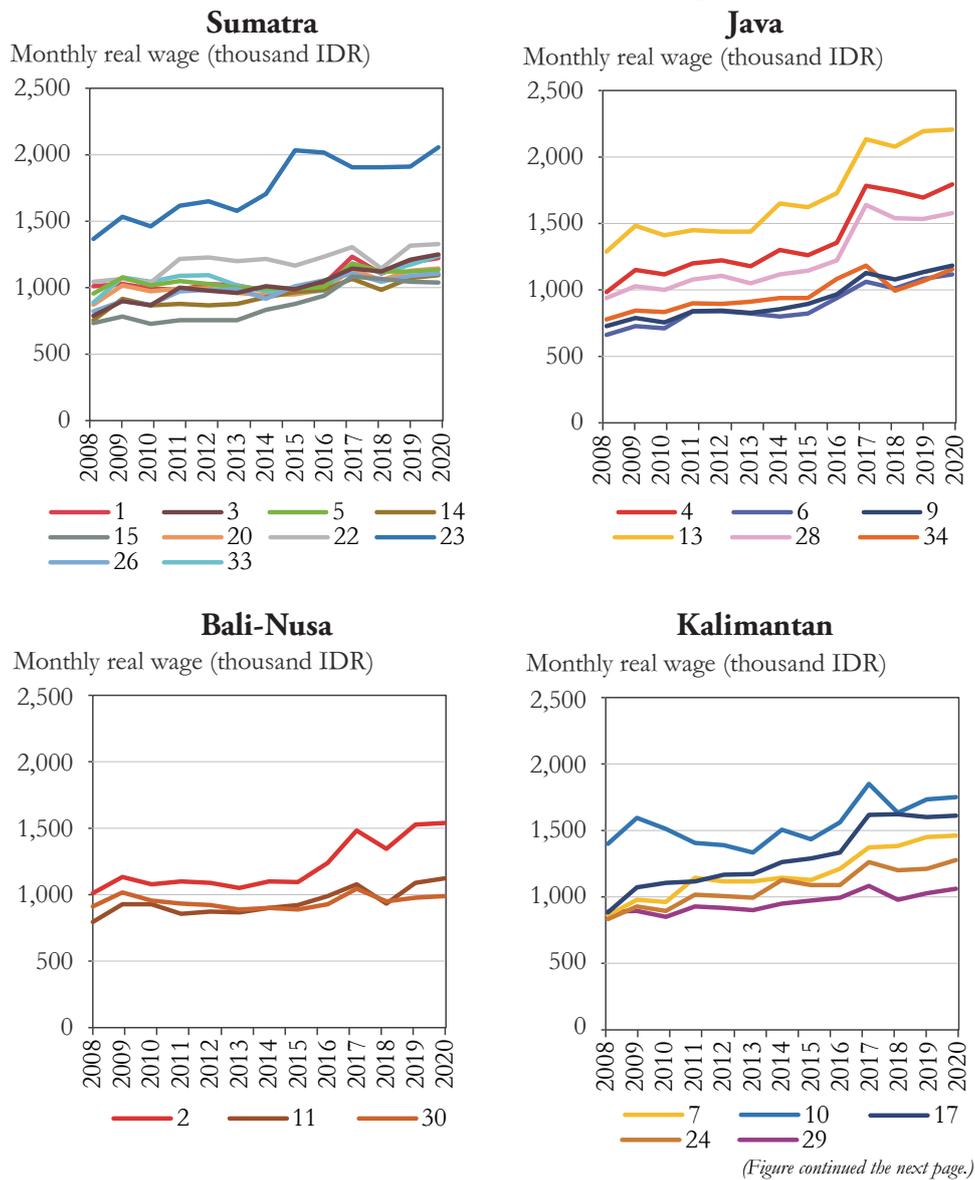
Descriptive statistics of monthly real wage in 34 Indonesian provinces

(thousand IDR)

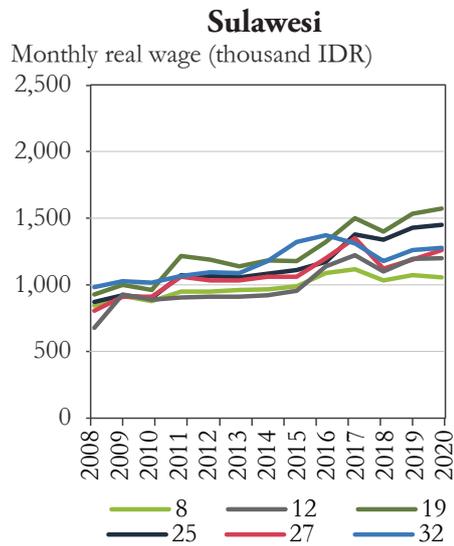
No.	Province	Mean	Std Dev	Min	Max
1	Aceh	1,057	947	968	1,231
2	Bali	1,205	1,920	1,001	1,529
3	Bangka Belitung	1,017	1,339	784	1,248
4	Banten	1,371	2,831	987	1,797
5	Bengkulu	1,049	685	955	1,178
6	Central Java	885	1,484	668	1,123
7	Central Kalimantan	1,173	1,886	857	1,452
8	Central Sulawesi	989	824	849	1,120
9	East Java	929	1,553	734	1,185
10	East Kalimantan	1,537	1,583	1,324	1,839
11	East Nusa Tenggara	938	486	880	1,037
12	Gorontalo	1,000	1,603	683	1,226
13	Jakarta	1,706	3,334	1,295	2,210
14	Jambi	941	975	755	1,092
15	Lampung	874	1,389	724	1,079
16	Maluku	1,191	793	1,075	1,370
17	North Kalimantan	1,290	2,435	880	1,613
18	North Maluku	1,205	1,060	985	1,373
19	North Sulawesi	1,243	2,143	929	1,571
20	North Sumatra	1,009	829	872	1,142
21	Papua	1,612	1,656	1,280	1,900
22	Riau	1,188	976	1,036	1,322
23	Riau Islands	1,744	2,329	1,365	2,051
24	South Kalimantan	1,066	1,402	830	1,269
25	South Sulawesi	1,145	1,978	876	1,452
26	South Sumatra	987	912	818	1,105
27	Southeast Sulawesi	1,079	1,495	810	1,350
28	West Java	1,233	2,490	942	1,645
29	West Kalimantan	954	696	845	1,077
30	West Nusa Tenggara	936	985	785	1,115
31	West Papua	1,551	1,053	1,384	1,732
32	West Sulawesi	1,170	1,304	986	1,377
33	West Sumatra	1,061	990	885	1,235
34	Yogyakarta	968	1,254	784	1,189

Figure A1

The time-series of monthly real wage across the 34 Indonesian provinces based on region*



(Continued.)



* The names of the provinces see in Table A1.

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