Regional Income Disparities and Convergence Clubs in Indonesia: New District-Level Evidence 2000-2017

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Abstract

This paper aims to re-examine the regional convergence hypothesis on income in Indonesia over the 2000-2017 period. By applying a non-linear dynamic factor model, this paper tests the club convergence hypothesis using a novel dataset of income at the district level. The results show significant five convergence clubs in Indonesian districts' income dynamics, implying the persistence of income disparity problems across districts even after implementing the decentralization policy. The subsequent analysis reveals two appealing features regarding the convergence clubs. First, districts belonging to the same province tend to be in the same club, and second, districts with specific characteristics (i.e., big cities or natural resources-rich regions) dominate the highest income club. Overall, our findings suggest some insightful policy implications, including the importance of differentiated development policies across convergence clubs and inter-provincial development strategies.

Keywords: Regional inequality, Convergence, Indonesia

JEL Codes: O40, O47, R10, R11

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1. Introduction

There is a growing recognition that reducing income inequality fosters sustainable development. Specifically, lower levels of income inequality not only prevent social conflict, but they are also a prerequisite for achieving social justice. On the other aspects, some studies also find that income inequality negatively affects economic growth (Barro, 2008; Ostry et al., 2014; van der Weide and Milanovic, 2018). Moreover, widening income inequality gives significant implications for economic growth as well as macroeconomic stability (Dabla-Norris et al., 2015).

As one of the most heterogeneous countries in the world, Indonesia consists of hundreds of ethnic groups with many different cultures and religious beliefs spreading throughout the world's largest archipelago. In economic terms, the country has been experiencing high regional inequality that persist since its independence. The inequality is shown by the most developed region, particularly in Java and Sumatra islands with capital intensive processing industries and the isolated regions that are barely connected to few regions (Hill, 1991). Therefore, one of the main challenges in Indonesia's development context is how to reduce regional inequality and foster regional convergence (Mishra, 2009).

The concern about regional inequality became greater when the decentralization policy was implemented in 2000 (Nasution, 2016; Mahi, 2016). The worry seems to be reasonable since the decentralization process in Indonesia was implemented without much preparation, in the sense that it was not accompanied by adequate institutional capacity or skilled officials at the local level (Brodjonegoro, 2004; Nasution, 2016). Some studies even argue that decentralization contributes to the negative growth of investment (Brodjonegoro, 2004; Tijaja and Faisal, 2014) owing to increased policy inconsistency and business uncertainty at the regional level. Motivated by the limited research and an inconclusive answer about the effect of decentralization on the regional income disparity dynamics, this paper studies the evolution of regional income disparities and prospects for convergence across 514 districts of Indonesia over the 2000-2017 period.

This study focuses on the period after the year 2000 because it corresponds to the beginning of Indonesia's decentralization era. In this era, the state budget is allocated to regions, both to provincial and municipal governments. However, the expected outcome from the decentralizing policy in reducing regional inequality has yet to be seen clearly, partly due to the diverse growth barriers and economic preconditions in each region. Hence, identifying groups of regions facing similar challenges is of particular relevance concerning the formulation of policies aiming to reduce regional disparities.

In brief, the results of this paper show that Indonesian districts form five convergence clubs, implying that the growth of income per capita in 514 districts can be clustered into five common trends. This study also finds a "catching-up effect" within each club where the initially poor districts tend to grow faster than the initially rich districts. Further analysis reveals two appealing features about the convergence clubs. First, districts belonging to the same province tend to be in the same convergence club. Second, the highest income club is dominated by districts with specific characteristics such as big capital cities or resources-rich regions. Furthermore, the implementation of classical convergence tests provides supplementary evidence about convergence speed within each club.

This paper contributes to the regional convergence literature in three following ways. First, it is based on a convergence framework that emphasizes the role of regional heterogeneity and the potential existence of multiple convergence clubs. The results of club convergence analysis are complemented by two classical tests of convergence, which are implemented for each identified club. Second, the analysis is based on a newly constructed dataset of per-capita income that covers 514 Indonesian districts over the 2000-2017 period. This granular perspective opens the possibility of identifying new patterns, which may remain hidden when using province-level data. Finally, we extend our analysis by applying a classical convergence test for all convergence clubs to inform the convergence patterns.

The remainder of this paper is organized as follows. Section 2 discusses the related literature about regional disparities and convergence in Indonesia. Section 3 explains our research methodology, while section 4 presents the data and some stylized facts. The results of the formation of convergence clubs are presented in Section 5. Section 6 discusses the results in the context of classical convergence indicators, the spatial distribution of the clubs, and policy issues. Finally, Section 7 closes the paper with concluding remarks.

2. Related literature

2.1 Regional income disparities in Indonesia

A large body of research has been conducted to analyze economic disparity among regions in Indonesia. Most of the studies argue that the large socio-economic disparities among regions in Indonesia are due to larger unequal economic activities, public infrastructure availability as well as resource endowment (Esmara, 1975; Akita, 1988; Garcia and Soelistianingsih, 1998; Hill et al., 2008). One of the pioneers of regional income disparities analysis in Indonesia at the provincial level was conducted by Esmara (1975). He studies the inequality of Indonesian economic development during 1970's by analyzing per capita Gross Domestic Product (GDP) without mining sector. The study finds that non-mining per capita income differed by a factor of 12 between the highest and the lowest income region.

Using Williamson Index, Akita and Lukman (1995) argue that regional inequality at the provincial level, measured by GDP per capita, had decreased during 1975-1992. However, using non-mining GDP per capita, the regional inequality in the same period remained relatively stagnant. Using a more extended period, Akita et al. (2011) examine the inter-provincial regional income disparities over the 1983-2004 period. The study indicates a large regional gap among the main islands in Indonesia. In addition, they also find large disparities across districts within provinces in the islands.

Moving to the different levels of observation, Tadjoeddin et al. (2001) analyze the regional inequality at the district level by examining the Theil and Gini coefficients of GDP per capita from 1993 to 1998. The study shows that regional disparities in Indonesia are stable at the district level during the period of analysis. Similarly, the study of Hill et al. (2008) finds that regional disparities remained relatively unchanged during 1993-1998. However, when oil and gas GDP per capita is excluded from the analysis, the regional inequality kept increasing slightly until 1998.

In the context of the post-Asian Financial Crisis (AFC) 1997/98 era, Aritenang (2014) argues that the implementation of the decentralization policy has been considered to increase regional disparities. According to the decentralization law, districts with abundant natural resources earn a higher share of revenue than their provincial government and their peers in the same province. Therefore, a natural resources-rich district receives a higher revenue share and tends to grow faster. In the end, this might increase disparities among districts.

2.2 Regional income convergence

A central prediction of the standard neoclassical growth model is that under common preferences and technologies, economies would tend to converge to a common long-run equilibrium (Barro and Sala-I-Martin, 1992; Mankiw et al., 1992; Islam, 2003; Barro and Sala-I-Martin, 2004).[1] There is a large literature that aims to test this prediction both across and within countries. Compared to national economies, the administrative regions within a country are more likely to share common preferences, technologies, and institutions. Thus, empirically testing for income convergence across regions within a country has become a central topic in the regional growth literature.

The seminal contributions of Barro (1991) and Barro and Sala-I-Martin (1992) document regional income convergence across the states in the United States, the prefectures of Japan, and the subnational regions of Europe. Interestingly, in all these cases, regions appear to be converging at a similar speed: 2% per year. These convergence dynamics imply that regional differences within each country would be halved in about 35 years (Abreu et al., 2005). These results have triggered a large empirical literature that aims to test the regional convergence hypothesis (Sala-I-Martin, 1996a; Magrini, 2004, 2009). From a methodological perspective, most papers evaluate convergence using two complementary analyses. On the one hand, an analysis of sigma (σ) convergence evaluates whether the income dispersion decreases over time. On the other, an analysis of beta (β)

[1]Although the original conception of the Solow growth model aims to explain the evolution of a single economy over time, its convergence prediction has been empirically tested across multiple countries, regions, industries, and firms. As a result, the convergence hypothesis has been studied from multiple perspectives. The recent work of Johnson and Papageorgiou (2020) provides a survey of the cross-country convergence literature. Magrini (2004) provides a survey of the regional convergence literature. The work of Rodrik (2013) is one of the most influential papers in the industrial convergence literature, and the work of Bahar (2018) evaluates convergence across firms.

convergence evaluates whether initially poor economies grow faster than initially rich regions. These two analyses are also related in the sense that beta convergence is necessary but not sufficient for sigma convergence (Sala-I-Martin, 1996a).

More recently, the convergence literature has been shifting its focus from the classical emphasis on average behavior and common long-run equilibrium to a new emphasis on heterogeneous behavior and multiple equilibria (Apergis et al., 2010; Bartkowska and Riedl, 2005; Zhang et al., 2019). This approach emphasizes the notion that, even within countries, there could be persistent differences in endowments, preferences, and technologies. As such, regional economies may not smoothly converge to a unique long-run equilibrium, but instead, multiple convergence clubs may characterize the regional economic system.

2.3 Regional income convergence in Indonesia

Many scholars have conducted studies on inequality at the regional level in Indonesia using various convergence frameworks (see Table 1). Garcia and Soelistianingsih (1998) employ beta convergence method to investigate the existence of convergence in income per capita across provinces during 1975-1993. The study shows that regional income disparities tend to converge, and it may take between thirty to forty years to reduce income differences by half. However, Hill et al. (2008) argue that the results of convergence by Garcia and Soelistianingsih (1998) are sensitive to the period analyzed and the unstable performance of the oil and gas sector. Also, the study of Hill et al. (2008) shows that during the financial crisis and its aftermath, that is from 1997 to 2002, there was no significant convergence at the regional level. Similarly, using conventional estimation of sigma and beta convergence, Tirtosuharto (2013) does not find regional convergence during the Asian financial crisis, the recovery period, and the beginning of the decentralization era.

At the district level, the study by Akita (2002) shows a similar conclusion that regional income inequality increased during 1993-1997. This result does not contradict other studies at the provincial level since it shows that inequality increased among certain districts within some provinces. In addition, Akita et al. (2011) show that when the Asian financial crisis hit in 1997, regional inequality has declined since some big cities were hit harder than less developed districts. However, during the recovery period, regional inequality increased again until 2004 and remained uncertain afterwards.

Analysis at the district level has also been conducted by Aritenang (2014) using exploratory analysis, Spatial Autoregressive (SAR) Lag Model, and Spatial Error Model (SEM) to capture the spatial effects. By considering the role of the neighborhood, the study finds that the convergence rate is higher throughout the decentralization era. A similar approach was conducted by Vidyattama (2013). However, the result of the study indicates inconclusive finding on convergence. The Williamson index measurement shows slight increases, although insignificant, while the beta convergence estimates reveal convergence at both the district and the provincial levels during 1999-2008. In addition, the study needs a longer period of observation since the overall trend of convergence is still very weak.

Another recent study was conducted by Kurniawan et al. (2019) by applying club convergence analysis on provincial dataset from 1969 to 2012. In their study, some missing data at the provincial level are interpolated in order to build a balanced panel dataset. The results show two convergence clubs in terms of all investigated variables.[2] Using a similar method, Mendez and Kataoka (2020) examine the disparities in

[2]The study examines the dynamics of four socio-economic indicators: per capita gross regional product, the Gini coefficient, the school enrolment rate, and the fertility rate.

Table 1: Studies on per capita income convergence in Indonesia

Author(s)	Observation	Methods	Findings
Garcia and Soelistianingsih (1998)	(26 provinces) 1975-1993 1980-1993 1983-1993	Absolute and conditional beta convergence	Results: Absolute convergence; conditional convergence increases convergence speed.
Akita (2002)	(27 provinces and 303 districts) 1975-1983 1983-1993 1993-1999	Williamson's weighted coefficient of variation (CVw) and Theil index	Results: Convergence at province and no convergence at district level. The mining sector matters and income inequality at the district level increases in1993-1997.
Hill et al. (2008)	(26 provinces) 1975-2004	Unconditional and conditional beta convergence	Results: Convergence before the Asian Financial Crisis (AFC) 1997 and no convergence after the AFC. The speed of convergence declines along with the decreasing in the mining sector.
Akita et al. (2011)	(26 provinces) 1983-2004	Bi-dimensional decomposition	Results: Convergence before the AFC 1997 and no convergence after the AFC. The convergence before the AFC is due to poorer performance of the resource-rich provinces.
Tirtosuharto (2013)	(26 provinces) 1997-2000 2001-2012	Sigma convergence and unconditional beta convergence	Results: No sigma convergence, beta convergence in 1997-2000 and no beta convergence in 2001-2012.
Vidyattama (2013)	(26 provinces and 294 districts) 1999-2008	Unconditional beta convergence, Spatial Autoregressive Lag, and Spatial Error Model	Results: Insignificant convergence in income per capita and significant convergence in HDI at both province and district levels.
Aritenang (2014)	(292 districts) 1994-2004 1994-2000 2001-2004	Spatial autocorrelation, Spatial Error Model, and Spatial Autoregressive Lag Model	Results: Strong evidence of spatial autocorrelation, the convergence rate is higher during decentralization.
Kurniawan et al. (2019)	(33 provinces) 1969-2012	Club convergence	Results: Two convergence clubs in four socio-economic indicators.
Mendez and Kataoka (2020)	(26 provinces) 1999-2010	Club convergence	Results: Two convergence clubs in labor productivity, four clubs in physical capital, two clubs in human capital, and unique convergence club in efficiency.

Source: Authors' documentation from many sources.

labor productivity, capital accumulation, and efficiency across 26 provinces from 1990 to 2010. The study finds that labor productivity, physical capital, and human capital are characterized by two, four, and two convergence clubs, respectively. Meanwhile, a unique convergence club is found to be related to the efficiency variable. The study suggests the importance of capital accumulation and efficiency improvements in promoting productivity growth as well as reducing the disparities among regions in Indonesia.

3. Methodology

3.1 Classical beta and sigma convergence

The most common method of convergence analysis is mainly based on classical models such as namely sigma convergence and beta convergence (Bernard and Durlauf, 1995; Hobijn and Franses, 2000; Phillips and Sul, 2007). Sigma convergence refers to the decreasing in growth dispersion (in most cases, the growth of income per capita) across countries or regions over time. Differently, beta convergence is seen in negative correlation between the initial level of income capita and its growth. Implicitly, this means that low-income countries tend to grow relatively faster than high-income countries and thus are able to catch up (Barro, 1991; Barro and Sala-I-Martin, 1992).

The concept of beta convergence can be differentiated into absolute and conditional convergence (Islam, 1995, 2003; Mankiw et al., 1992; Sala-I-Martin, 1996b). On one side, absolute beta convergence assumes that countries will approach a particular common steady-state growth path over time, given the variability in the initial condition of each country. On the other side, the notion of conditional beta convergence implies convergence occurs towards different paths of steady-state growth given the assumption that countries have distinctive characteristics, such as accumulation in human and physical capital, institution, economic and political system, and other factors affecting economic growth. Many researchers find that the dispersion of income per capita across economies follows the patterns of clusters rather than the direction of a common growth path (Quah, 1996; Phillips and Sul, 2009; Basile, 2009). This is not only true for largely diversified cases such as cross country analysis, but this trend has also been observed in more integrated economies like those in Western Europe (Corrado et al., 2005).

Some studies also started to find convergence patterns across countries, regions, industries, etc., when analyzing socio-economic variables (Barro, 1991; Barro and Sala-I-Martin, 1992). According to Barro and Sala-I-Martin (1992), this convergence pattern can be generalized as follows:

$$(1/T) \cdot log\frac{y_{iT}}{y_{i0}} = \alpha - \frac{[1 - e^{-\beta T}]}{T} \cdot log(y_{i0}) + w_{i,0T} \tag{1}$$

where y is the analyzed variable, i represents a region, 0 and T are the initial and final times, β is known as the speed of convergence, α includes unobserved parameters including the steady-state and $w_{i,0T}$ is the error term. Referring to equation (1), if there are robust signs of beta convergence, then a different parameter known as the "half-life" can be defined as follows:

$$half \cdot life = \frac{log2}{\beta} \tag{2}$$

This parameter indicates the time required for the average region to reduce the gap between its initial and the final equilibrium state by half.

3.2 Relative convergence test

Phillips and Sul (2007) develop log t convergence test, an innovative method to investigate the existence of multiple convergence clubs based on a clustering algorithm. This method is favorable because of its superiority in the sense that it allows the time series not to be co-integrated, thus allowing individual observation to be transitionally divergent (Bartkowska and Riedl, 2005). The method also concludes that the absence of co-integration in respective time series does not necessarily deny the existence of convergence (Phillips and Sul, 2007). Due to its advantages, numerous researchers have utilized this approach with applications in convergence analysis on various economic indicators such as per capita income, financial development, and energy.

The relative convergence test suggested by Phillips and Sul (2007, 2009) is based on the decomposition of the panel-data variable of interest in the following way:

$$y_{it} = g_{it} + a_{it} \tag{3}$$

where g_{it} is a systematic component and a_{it} is a transitory component.

To separate common from idiosyncratic components, equation 3 can be transformed with a time-varying factor as follows:

$$y_{it} = \left(\frac{g_{it} + a_{it}}{\mu_t}\right)\mu_t = \delta_{it}\mu_t \tag{4}$$

where δ_{it} contains error term and unit-specific component and thus represents an idiosyncratic element that varies over time, and μ_t is a common component.

To be more specific, the transition path of an observed economy towards its own equilibrium growth path is explained by δ_{it}, while μ_t depicts a hypothesized equilibrium growth path that is common to all economies.

Equation 4 is therefore a dynamic factor model containing a factor loading coefficient δ_{it} that represents the idiosyncratic distance between a common trending behavior, μ_t, and the dependent variable, y_{it}. Furthermore, to characterize the dynamics of the idiosyncratic component, δ_{it}, Phillips and Sul (2007) propose the following semi-parametric specification:

$$\delta_{it} = \delta_i + \frac{\sigma_i \xi_{it}}{log\,(t)\,t^{\alpha}} \tag{5}$$

where δ_i represents the heterogeneity of each economy but constant over time, ξ_{it} is a weakly time-dependent process with mean 0 and variance 1 across economies. Under the condition given in equation 5, convergence occurs when all economies move to the same transition path as such,

$$\lim_{t\to\infty} \delta_{it} = \delta \quad \text{and} \quad \alpha \geq 0 \tag{6}$$

In order to estimate the transition coefficient δ_{it}, Phillips and Sul (2007) construct a relative transition parameter, h_{it}, as

$$h_{it} = \frac{y_{it}}{\frac{1}{N}\sum_{i=1}^{N} y_{it}} = \frac{\delta_{it}}{\frac{1}{N}\sum_{i=1}^{N} \delta_{it}} \tag{7}$$

where the common component, μ_t in equation 4 is eliminated by dividing the independent variable, y_{it}, with the panel average. Thus, h_{it} represents the transition path of economy *i* against the level of cross-sectional average, implying the calculation of individual economic behaviors relative to other economies. Then, h_{it} converges to unity, that is $h_{it} \to 1$, when $t \to \infty$.

Later, the notion of convergence can be transformed into the following equation that describes the cross-sectional variance of h_{it},

$$H_t = \frac{1}{N}\sum_{i=1}^{N} (h_{it} - 1)^2 \to 0 \tag{8}$$

where the cross-sectional variance converges to zero, $H_t \to 0$.

The null hypothesis in equation 6 is verified in counter to the alternative hypothesis $H_A : \delta_i \neq \delta$ for all *i* or $\alpha \geq 0$. Finally, Phillips and Sul (2007) empirically evaluate this null hypothesis by using the following log *t* regression model:

$$\log\left(\frac{H_1}{H_t}\right) - 2\log\{\log(t)\} = a + b\,\log(t) + \varepsilon_t \qquad (9)$$
$$\text{for} \quad t = [rT], [rT]+1, \ldots, T \quad \text{with} \quad r > 0$$

where rT is the initial observation in the regression, which implies that the first fraction of the data (that is, *r*) is discarded.

Based on Monte Carlo experiments, Phillips and Sul (2007) suggest applying $r = 0.3$ when the sample is small or moderate $T \leq 50$. A fairly conventional inferential procedure is also suggested for equation 9. To be more specific, a one-sided *t* test with heteroskedasticity-autocorrelation consistent (HAC) standard errors is used. In this setting, the null hypothesis of convergence is rejected when the t-statistics ($t_{\hat{b}}$) is smaller than -1.65.

3.3 Clustering algorithm

Even though the null hypothesis of overall convergence in the full sample is rejected, it does not necessarily mean that the convergence in the subsample of the panel is not present. Therefore, following Phillips and Sul (2007), we exploit the feature of the model in equation 7 to reveal the presence of multiple convergence clubs in subsample. For that purpose, we use an innovative data-driven algorithm developed by Phillips and Sul (2009), which can be summarized in the following four steps:

1. *Ordering*: Sample units (districts) are arranged in a decreasing order according to their observation in the last period. In this paper, the

ordering is conducted using the average of the last $\frac{1}{3}$.

2. *Constructing the core group*: A core group of sample units (districts) is identified based on the first *k* unit of the panel data set $(2 \leq k \leq N)$. If the $t_{\hat{b}}$ of the *k* unit is larger than -1.65, the core group formation is established. If the $t_{\hat{b}}$ in the first *k* unit is smaller than -1.65, the first unit is dropped, and then the log *t* test for the next units is conducted. The step is continued until the $t_{\hat{b}}$ of the pair units is larger than -1.65. If there are no pairs of units showing $t_{\hat{b}}$ larger than -1.65 in the entire sample, it can be concluded that there are no convergence clubs in the panel.

3. *Deciding club membership*: Sample units (districts) not belonging to the core group are re-evaluated once at a time with log *t* regression. A new group is formed when the $t_{\hat{b}}$ is larger than -1.65. Otherwise, if the additional units give a result that $t_{\hat{b}}$ is smaller than -1.65, then the convergence club only consists of the core group.

4. *Iteration and stopping rule*: The log *t* regression is applied for the remaining sample units (districts). If the process shows the rejection of the null hypothesis of convergence, steps 1 to 3 are performed again. The remaining sample units (districts) are labeled as divergent if no core group is found, and the algorithm stops.

The representation of the relative transition curve for different economies in the club convergence framework can be illustrated in Figure 1. The figure clearly shows that the transition curves for different regions form a funnel. The four regions, which are region A, B, C, and D, differ in their initial conditions as well as in their transition paths. However, region A and region B's relative transition curve converge into the same value, which is Club 1. In comparison, region C and region D are characterized by

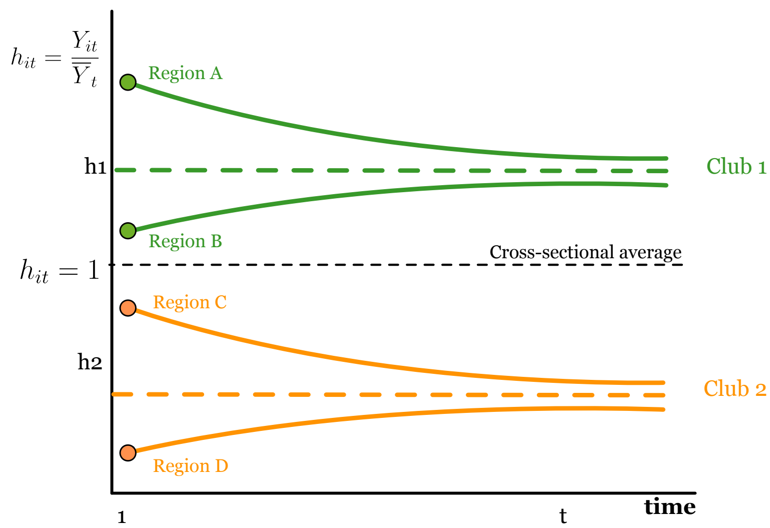


Figure 1: An illustration of transition paths and convergence clubs

medium and low initial conditions, consecutively reflecting a typical developing region with a slow growth rate and a poor region that grows rapidly. With time, the transition path of both regions converge into Club 2.

4. Data and stylized facts

4.1 Data construction

This study uses annual GDP per capita at the district level from 2000 to 2017. However, not all of the data are available for every year in each district. In addition, there are some missing observations caused by the splitting up of new districts during the decentralization period. Since the club convergence test of Phillips and Sul (2007) requires balanced panel data, we constructed a balanced panel dataset of 514 districts by solving the missing observations through interpolation/imputation.[3] Similar with the study of Kurniawan et al. (2019), the imputation process in our study was conducted using a linear regression method with the year and reference districts as candidates of regressors. Hence, since we only predicted the missing values from its trend, it would not significantly alter the convergence results.[4] Table 2 shows the descriptive statistics of the dataset.

Table 2: Descriptive statistics

	Mean			Standard deviation			Max/Min	
	2000	2017	2000/2017	2000	2017	2000/2017	2000	2017
GDP per capita (in thousand IDR)	25,032	36,041	0.69	62,172	42,823	1.45	465.40	105.05
Log of GDP per capita	9.57	10.20	0.94	0.81	0.67	1.20	1.81	1.56
Trend log of GDP per capita	9.57	10.20	0.94	0.81	0.68	1.20	1.81	1.56
Relative trend of log GDP per capita	1.00	1.00	1.00	0.08	0.07	1.28	1.81	1.55

As mentioned in the methodology, we transformed the GDP per capita data into a log form. Like common macroeconomic data, the GDP per capita has two prominent features, which are long-run growth trends in aggregate and a cyclical component that represents fluctuations in the shorter periods, known as the business cycles. When analyzing business cycles in observed data by regression or filtering, it is necessary to isolate the cyclical component from the trend (Phillips and Shi, 2019). Therefore, following Uhlig and Ravn (2002), we filtered the GDP per capita series using Hodrick-Prescott (HP) filter technique with smoothing parameter (λ) equals to 6.25.

[3] We combined actual data of the new districts and the reference districts and compared them to ensure that measurement error caused by the interpolation is minimum. Details of this interpolation process are provided in Appendix A.

[4] For the robustness check of our interpolation results, we implemented sigma and beta convergence tests using the number of districts in the year 2000 (342 districts). As reported in Appendix E, we found no significant difference in sigma and beta convergence coefficients between the full sample of 514 districts and the smaller number of districts.

4.2 Stylized facts on regional disparities in Indonesia

This subsection illustrates how income disparities across districts in Indonesia have evolved over time. Figure 2 measures regional disparities as the standard deviation of the log of GDP per capita. This measurement approach is commonly used in the regional growth literature and is generally referred to as the study of sigma convergence (Barro and Sala-I-Martin, 1992; Magrini, 2004; Sala-I-Martin, 1996b). A process of sigma convergence occurs when regional disparities decrease over time. Figure 2 highlights this process by pointing out that the standard deviation of the log of GDP per capita has been systematically decreasing over the 2000-2017 period.

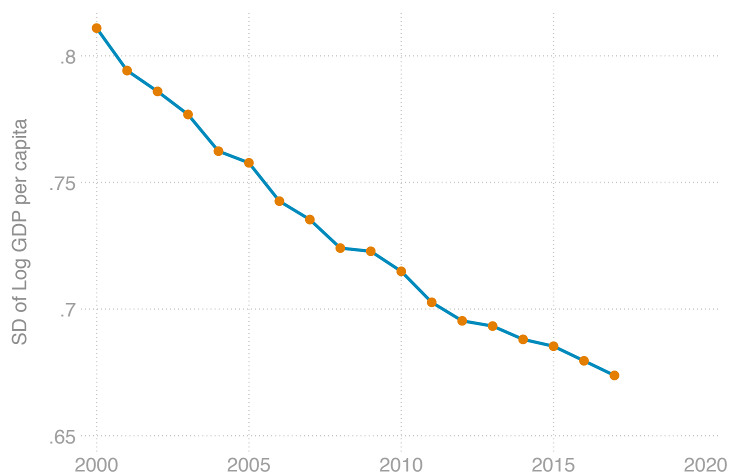


Figure 2: Evolution of regional disparities: Sigma convergence approach

Notes: GDP refers to the district-level gross domestic product, and it is measured based on constant prices of 2010. The source of the data is the Central Bureau of Statistics of Indonesia and interpolation results.

We also show the process where the initially poor regions are catching up and growing faster than initially rich regions. This catching-up process is largely documented in the economic growth literature and is referred to as the study of beta convergence (Barro and Sala-I-Martin, 1992; Magrini, 2004; Sala-I-Martin, 1996b). Figure 3 highlights this process by pointing out that regions with a low GDP per capita in 2000 have grown faster than initially rich regions over the 2000-2017 period. Interestingly, the richest regions in 1990 experienced large negative growth rates in subsequent years. Thus, the (beta) convergence process is arising not only because of the faster growth of the poorest regions but also because of a systematic reduction in the income of the richest regions.

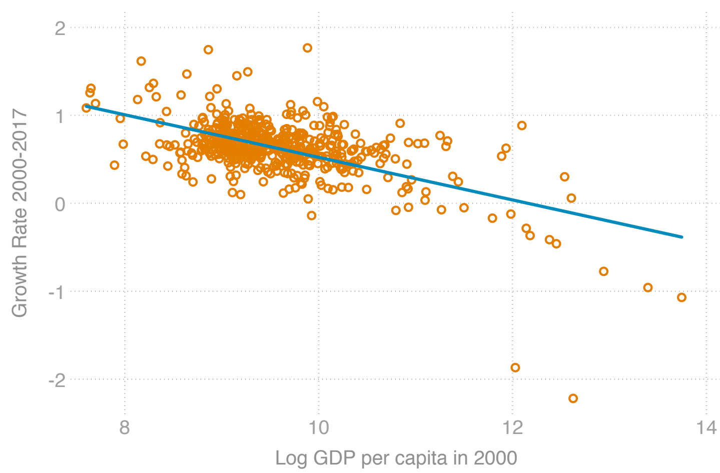


Figure 3: Evolution of regional disparities: Beta convergence approach

Notes: GDP refers to the district-level gross domestic product, and it is measured based on constant prices of 2010. The source of the data is the Central Bureau of Statistics of Indonesia and interpolation results.

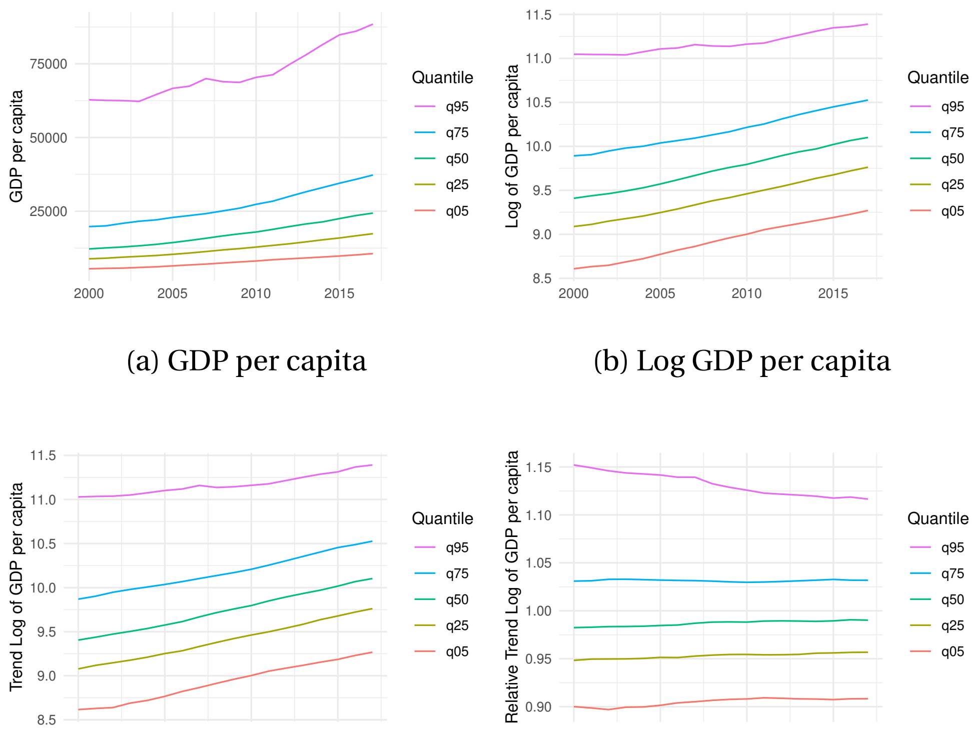
By construction, the summary statistics of sigma and beta convergence only describe the behavior of an average or representative economy (Magrini, 2004). They fail to describe more complex convergence dynamics that could occur beyond the mean of the income distribution. They also fail to accommodate the notions of multiple equilibria and convergence clubs, which could arise when the regions' performance is highly heterogeneous.

In Indonesia's context, a high degree of regional heterogeneity has been previously documented using province-level data. Moreover, it has been argued that only focusing on average patterns is likely to be incomplete at best or misleading at worst (Mendez and Kataoka, 2020). In an attempt to start documenting the degree of regional heterogeneity using district-level data of recent years, Figures 4 and 5 show the evolution of regional disparities beyond the scope of the average or median district.

Figure 4 shows how the quantiles of the distribution have evolved over time. Panel (a) indicates that when we evaluate the regional dynamics of GDP per capita, within any logarithm transformation, regional disparities have been increasing over time. Increasing disparities are evident not only when we measure the gap between the quantile 95 and quantile 5, but also when we measure the gap between the quantile 75 and 25. In the statistics literature, this latter gap is referred to as the interquartile range (IQR) and is commonly used as a dispersion statistic that is robust to extreme values.[5] Panels (b) and (c) indicate that the logarithm version of GDP per capita shows less diverging dynamics. Despite of this transformation, the IQR, which encompasses half of the entire distribution, shows very little signs of regional convergence. Panel (d) normalizes the trend of log GDP by the cross-sectional mean of each year. This transformation helps to remove the common increasing trends observed in panels (b) and (c). Based on this transformation, regional disparities have been evolving differently within the income distribution. Most of the reduction in the disparities arises from the tails of this distribution, particularly the upper tail. In contrast, disparities around the center of the distribution show little change. The size of the IQR has been almost constant over the entire 2000-2017 period.

Figure 5 provides a more detailed perspective on the dynamics reported

[5] In the convergence literature, the IQR is also used to study sigma convergence (Mendez-Guerra, 2018).



(a) GDP per capita

(b) Log GDP per capita

(c) Trend log GDP per capita

(d) Relative trend log GDP per capita

Figure 4: Evolution of regional disparities: Distributional quantile approach

Notes: GDP refers to the district-level gross domestic product, and it is measured based on constant prices of 2010. The source of the data is the Central Bureau of Statistics of Indonesia and interpolation results.

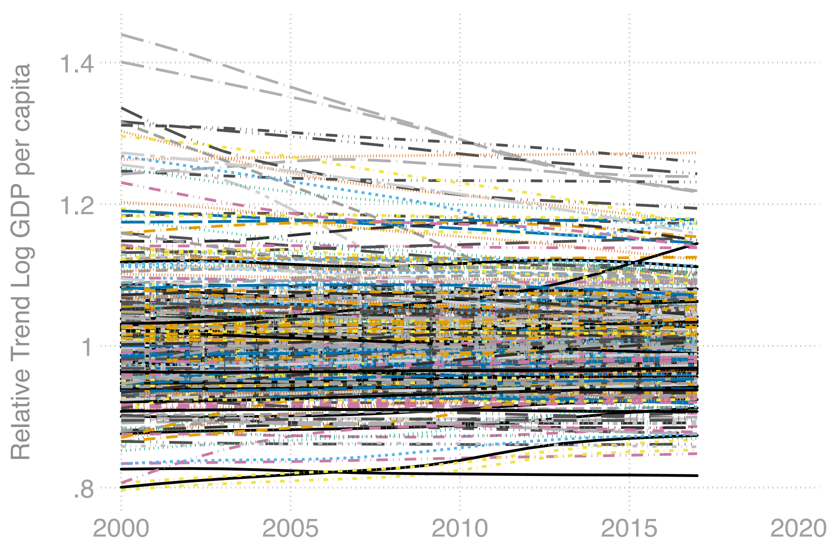


Figure 5: Evolution of regional disparities: Relative convergence approach

Notes: GDP refers to the district-level gross domestic product, and it is measured based on constant prices of 2010. The source of the data is the Central Bureau of Statistics of Indonesia and interpolation results.

in Figure 4d. Instead of just displaying five hypothetical regions, Figure 5 shows the actual dynamics of all regions.[6] Its main finding is consistent with that of Figure 4; that is, the process of regional convergence is not homogeneous across the distribution of districts. Regions at the top of the distribution are converging faster than those at the bottom. Regions around the middle of the distribution show little progress in the reduction of regional disparities.

5. Results

5.1 Relative convergence test

After applying the log t test to the income per capita data across 514 Indonesian districts over the 2000-2017 period, we were able to reject the null hypothesis of overall convergence at the 5% significant level, where $\hat{b}$ is significantly < 0 and $t_{\hat{b}}$ is -22.28 (see Table 3). This implies that convergence for all districts is not present, indicating that the income growth process of 514 Indonesian districts from 2000 to 2017 does not show a single equilibrium steady-state. This finding is consistent with the empirical evidence documented in the study of Hill et al. (2008), where no significant convergence was observed after the 1997/98 Asian financial crisis period, as opposed to significant convergence before the crisis.[7] Our finding also supports the study of Tirtosuharto (2013), who concludes the lack of regional convergence for the period from 2003 to 2012 following economic recovery from the Asian financial crisis and the beginning of the

[6] As regions can change their ranking in the income distribution, the quantiles of Figure 4 do not necessarily track the performance of a unique region over time.

[7] The study of Hill et al. (2008) shows the variability in the pace of beta convergence across subperiod during 1975-2002; 2% during the oil boom (1975-81), 2.8% in the era of major policy reforms (1981-86), 1.7% for the period 1986-92 as the export-oriented reforms took place, 1% during the 1990s, and no convergence in the crisis and post-crisis period.

decentralization era.

Table 3: Global convergence test

	Coefficient	Standard Error	t-statistic
log(t)	-0.52	0.02	-22.28

Note: The null hypothesis of convergence is rejected when the t-statistic is less than -1.65.

This lack of overall convergence also entails policy implications related to the implementation of the decentralization policy in Indonesia after the crisis. As pointed out by Azis (2008) and Nasution (2016), by and large, the performance of regional growth after the decentralization has been unsatisfying. One of the major causes of this unexpected outcome is the variability in the capacity of regional institutions and local leaders to leverage local resources, in addition to counterproductive policies issued by local governments (e.g., imposing hidden fees, allocating funds to unnecessary projects), and inflexible and over-regulated national policies. Therefore, to avoid potential detrimental effect of decentralization on regional disparities, in particular developing countries like Indonesia, the regional government is required to improve the quality of institutional factors such as accountability, people's empowerment as well as redistribution capacity (Azis, 2008; Rodriguez-Pose and Ezcurra, 2010).

5.2 Clustering algorithm and convergence clubs

Although overall convergence across Indonesian districts does not prevail, the log t test brings the possibility to observe the existence of several convergence clusters, as explained in Section 3.3. Therefore, we applied the test procedure to investigate convergence clubs. As shown in Table 4, we found five significant initial clubs.[8] The first convergence club consists of 6 districts; the second club consists of 126 districts; the third club consists of 178 districts; the fourth club contains 181 districts, and the fifth club consists of 23 districts. The rows correspond to the fitted coefficients and t-statistic in each club.

The order of the convergence clubs is sorted from the districts with the highest to the lowest GDP per capita, that is, Club 1 refers to the highest GDP per capita group and Club 5 displays the lowest GDP per capita group. The result of this club convergence test implies that the development of income per capita in 514 Indonesian districts can be grouped into five common trends during 2000-2017.

Table 4: Local convergence test

	Club1	Club2	Club3	Club4	Club5
Coefficient	0.42	-0.08	0.37	-0.04	0.49
t-statistic	4.97	-1.52	5.26	-1.60	6.55
N. of regions	6	126	178	181	23

Note: The null hypothesis of convergence is rejected when the t-statistic is less than -1.65.

Then, following Phillips and Sul (2009), we checked the possibility of whether any of those identified clubs can be merged to form larger convergence clubs.[9] As shown in Table 5, the club merging test result suggests that the convergence hypothesis is rejected ($\hat{b}$ is significantly < 0 and $t_{\hat{b}}$ is smaller than -1.65). Hence, the initial five clubs are confirmed as

[8] See Appendix B for complete members of each club.
[9] The clubs merging steps are outlined in Appendix C.

the final convergence clubs.

Table 5: Clubs merging test

	Club1+2	Club2+3	Club3+4	Club4+5
Coefficient	-0.14	-0.27	-0.30	-0.20
t-statistic	-3.08	-6.99	-15.44	-9.52

Note: The null hypothesis of convergence is rejected when the t-statistic is less than -1.65.

Furthermore, measuring the gap between clubs is also useful to understand the income disparities among convergence clubs. For this purpose, we show the mean per capita income of each club in the second column of Table 6. The statistics suggest that the gap of income per capita between clubs is arguably large, particularly between Club 1 and Club 2, where the average income per capita of districts in Club 1 is IDR 231 million, about four times larger than that in Club 2. This implies that Club 2 has very little progress in catching up with Club 1. Table 6 also reflects severe income inequality problems among districts in Indonesia, where the average income per capita in the last club is only about 3% of the that in the first club.

Table 6: Characteristics of the clubs 2000-2017

	Mean	Std. Deviation	Min	Max
Club 1	231,289	196,580	7,058	932,664
Club 2	56,961	58,557	7,718	658,303
Club 3	20,090	12,178	3,402	304,400
Club 4	13,469	7.952	4,005	194,717
Club 5	7,549	5.959	2,004	59,292

Note: The income per capita data is in a thousand IDR.

Figure 6 shows the transition paths of members in each club by comparing income per capita of each district (in log form) relative to clubs' average. All five clubs exhibit different convergence behaviors and transition paths within the club, depending on each district's initial conditions and development process. We also capture one asymmetric transition pattern within the club. On the one hand, some districts with a higher level of income at the initial period experience a sufficiently large income reduction at the final period and move downwards to the club's average level. Most of these districts are those relying on natural resources (e.g., mining and natural gas processing) such as Mimika (Club 1), Bontang (Club 2), Lhokseumawe (Club 3), Aceh Utara (Club 4), and Aceh Timur (Club 5). The last three districts also suffer from prolonged security issues that led to the Martial Law enactment in 2003, followed by the Tsunami disaster in 2004. On the other hand, none of the districts with a lower income level at the initial period record significant improvement. This asymmetrical pattern implies that the convergence process within clubs (particularly Club 4 and 5) is influenced by the depleting income in wealthier districts.

Similar to Figure 4d, in Figure 7 we plot the transition paths of clubs over time. However, instead of using the absolute income per capita (in log form) on Y axes, in Figure 7 we compare the transition of clubs relative to the cross-sectional average of all clubs. The parallel pattern of the clubs' transition path indicates that the clubs do not converge over time. Even though Club 3 appears to slightly close its gap to Club 2, the transition path of the other clubs reflects prolonged and stable dispersion between clubs, where Club 4 and 5 are systematically below the average, while Club 1 and 2 are consistently above the average.

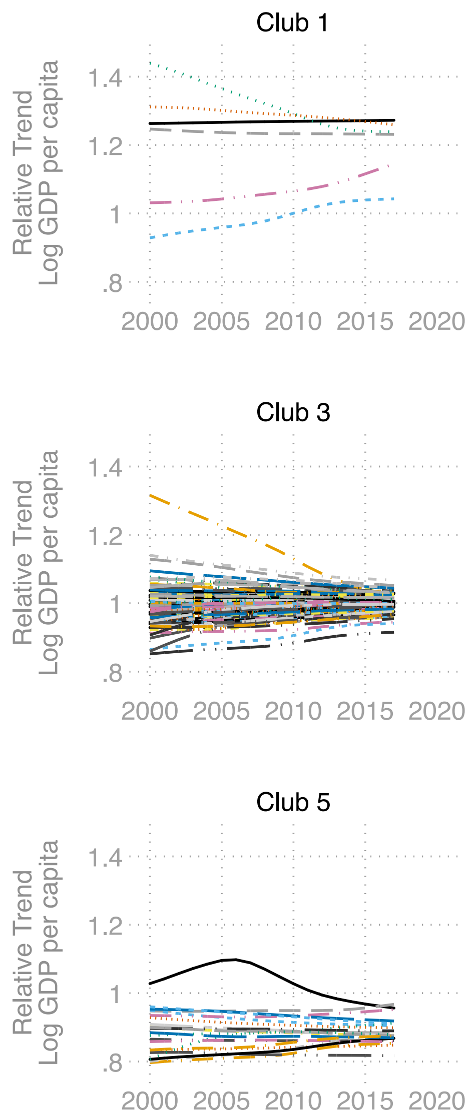


Figure 6: Convergence clubs and transition paths

Notes: GDP refers to the district-level gross domestic product, and it is measured based on constant prices of 2010. The source of the data is the Central Bureau of Statistics of Indonesia and interpolation results.

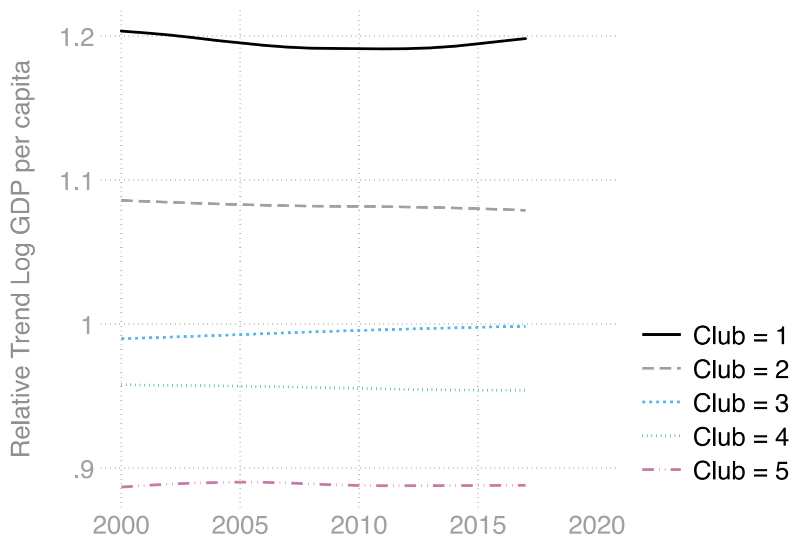


Figure 7: Convergence clubs trends

Notes: GDP refers to the district-level gross domestic product, and it is measured based on constant prices of 2010. The source of the data is the Central Bureau of Statistics of Indonesia and interpolation results.

5.3 Sensitivity to the trend estimation

We also implemented the log t test by using the smoothing parameter (λ) of Hodrick-Prescott (HP) filter equals to 400, which is used in the study of Phillips and Sul (2007). Similar to the results discussed in the previous section, the existence of global convergence is rejected at the 5% significant level ($\hat{b}$ is significantly < 0 and $t_{\hat{b}}$ is -23.02). Then we proceeded with the club convergence test by following the same procedures discussed in Section 3.3. We found twelve convergence clubs initially. Next, we applied the merging test procedure to investigate whether any of those initial subgroups can be merged to form convergence clubs with a larger number of members.

As a result, we also found five final significant convergence clubs. The

Table 7: Characteristics of the clubs, 2000-2017 (Trend parameter 400)

	Mean	Std. Deviation	Min	Max
Club 1	198,036	166,863	7,058	932,664
Club 2	50.595	39,595	3,531	417,149
Club 3	20,534	12,502	2,102	304,400
Club 4	11,825	3,505	4,292	59,292
Club 5	5,809	1,746	2,004	10,376

Note: The income per capita data is in a thousand IDR.

first and second initial clubs merge into first convergence club with 14 members while the third initial club becomes the second club with 106 members. Next, the third new club is formed by the fourth, fifth, and sixth initial clubs with 240 members and becomes the largest final club (47% of the total number of districts). Next, the fourth final club is constructed by clubs 7, 8, 9, 10, and 11 of the initial clubs with 132 members. Finally, the twelfth (the last) initial club stays unmerged with 22 members (details of results are presented in Appendix D). Consistent with the previous analysis, the statistics shown in Table 7 also imply a huge income gap among clubs. Referring to the average of per capita income in all clubs, one may quickly capture that the biggest income gap lies between Club 1 and Club 2, while the income gap between districts in lower clubs (Club 4 and Club 5) is much smaller.

6. Discussion

6.1 Convergence within clubs

This section evaluates the convergence patterns within each club using the classical frameworks of sigma and beta convergence. Figure 8 shows the evolution of the standard deviation of the log of GDP per capita for each club. All sub-figures share the same axes in order to facilitate comparability between clubs. Consistent with Figure 6, there is a stronger process of convergence within clubs than between clubs. In particular, the districts of Club 1 (see Appendix B for a detailed list) show the largest reduction in regional disparities. Although the other clubs start from lower levels of disparities, they show relatively less progress over time.

Figure 9 shows the negative relationship between the initial level of income and its subsequent growth rate. Within each club, initially poor regions are growing faster than initially rich ones. Thus, a process of beta convergence is also taking place within each club. Compared to the global convergence process suggested by Figure 3, the slope of each convergence club is steeper. This difference suggests that the (local) speed of convergence within each club is faster than that of the global process.

Table 8 provides further details about beta convergence within each club. Again, relative to the global fit (Figure 3), the fit of the local models is higher. The R-squared ranges from 0.64 in Club 5 to 0.86 in Club 1. The districts belong to Club 3 converge at the highest speed (5.3% per year). Thus, it is expected that disparities within Club 3 would be reduced by half in just under 13 years. This fast local convergence contrasts with the global model, which predicts that disparities would be halved in 42 years.

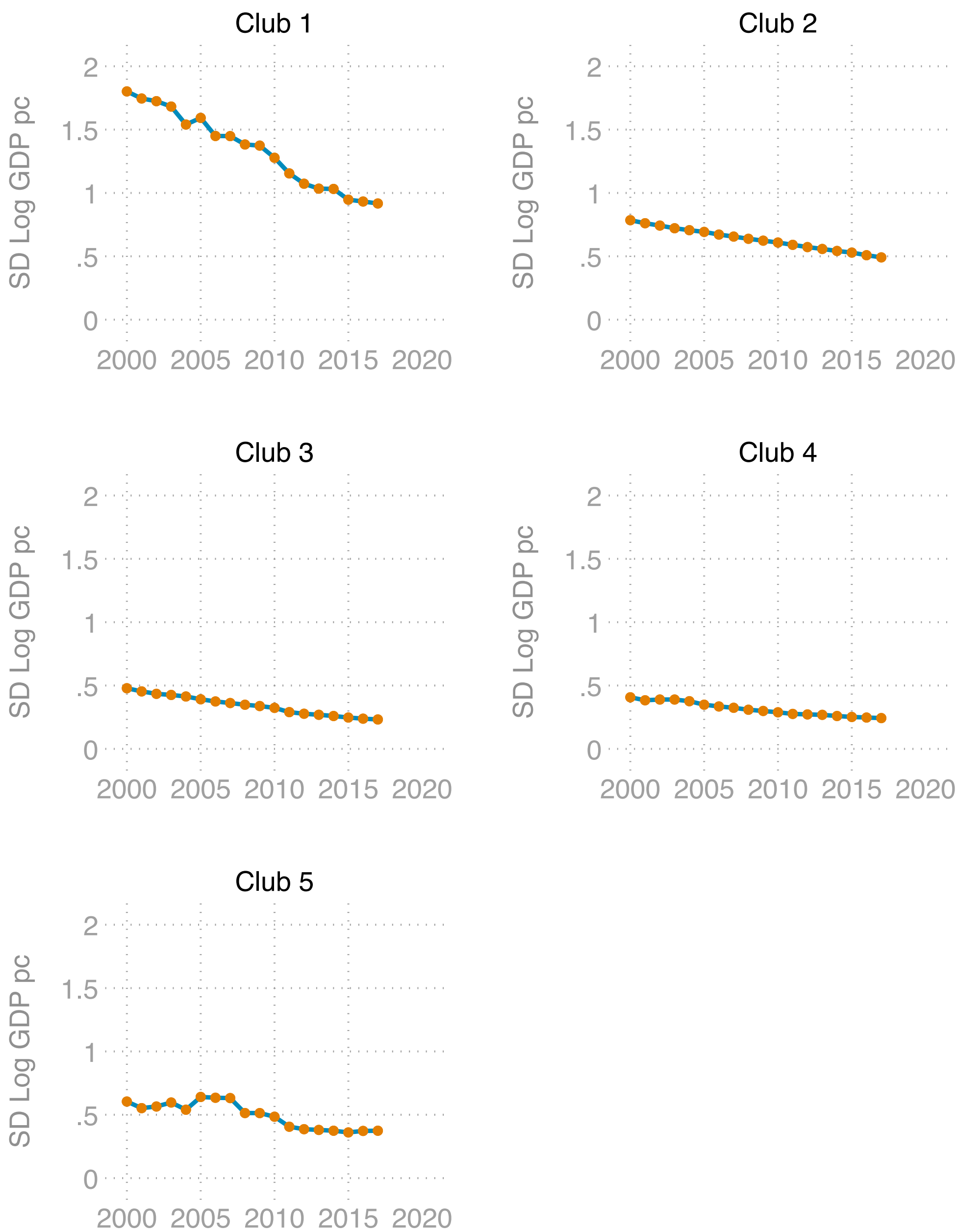


Figure 8: Evolution of disparities within clubs: Sigma convergence approach

Notes: GDP refers to the district-level gross domestic product, and it is measured based on constant prices of 2010. The source of the data is the Central Bureau of Statistics of Indonesia and interpolation results.

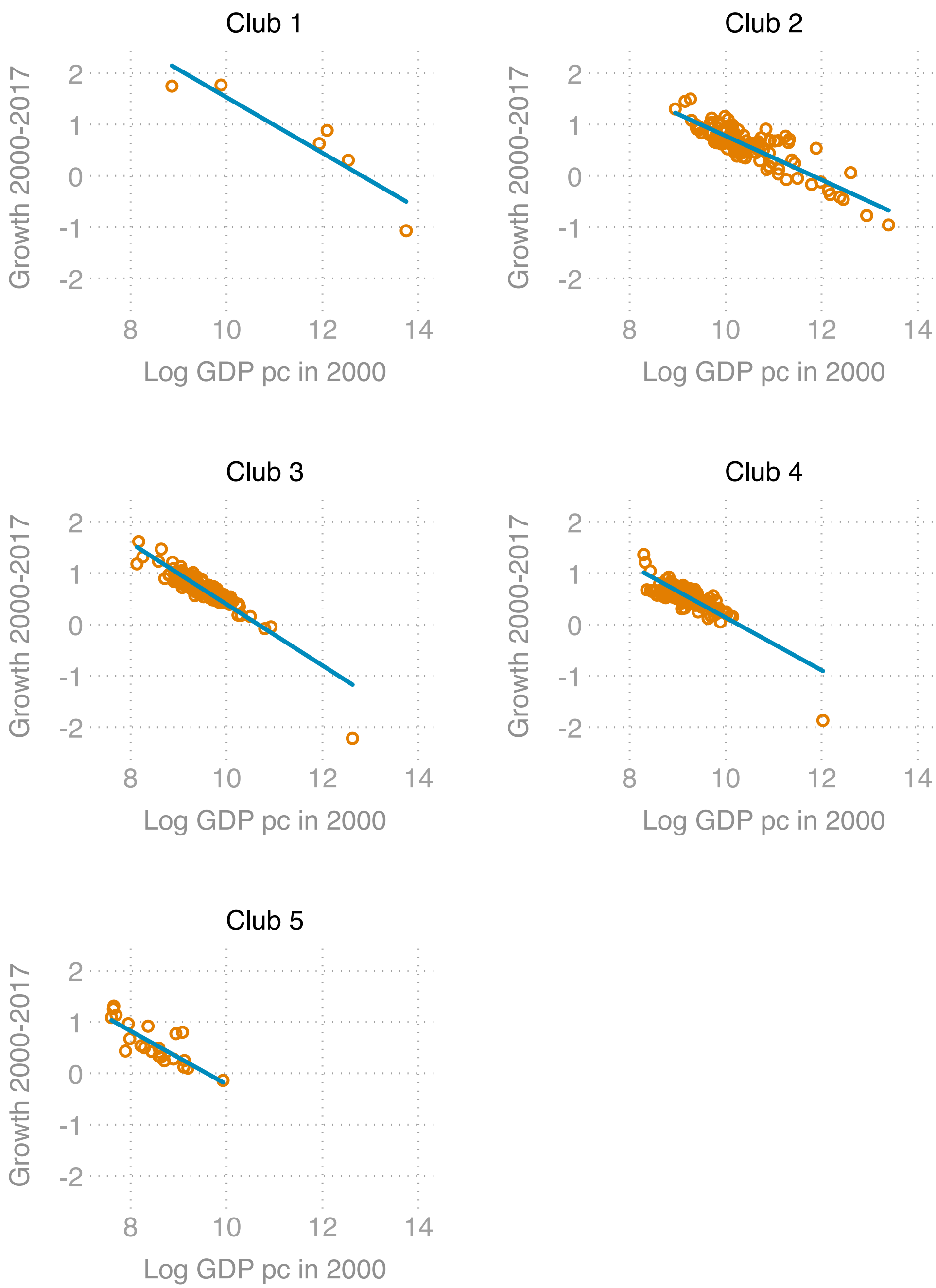


Figure 9: Evolution of disparities within clubs: Beta convergence approach

Notes: GDP refers to the district-level gross domestic product, and it is measured based on constant prices of 2010. The source of the data is the Central Bureau of Statistics of Indonesia and interpolation results.

Table 8: Evolution of disparities within clubs: Beta convergence approach

	Beta coefficient	Convergence speed	Half-life in years	R-square
Club 1	-0,54***	0,046	15,09	0,86
Club 2	-0,43***	0,032	21,14	0,74
Club 3	-0,59***	0,053	12,98	0,83
Club 4	-0,51***	0,042	16,36	0,69
Club 5	-0,52***	0,043	15,05	0,64

6.2 Geographical distribution of the convergence clubs

Now, we provide a geographical view of club membership as seen in Figure 10. A few regularities are visible from the map. First, the province effect is notably obvious; districts belonging to the same province tend to be in the same club (Barro, 1991; Quah, 1996). This pattern applies almost to all clubs. For example, districts in provinces of East Kalimantan and Riau tend to be grouped in Club 2. Similarly, Aceh, West Sumatra, West Kalimantan, and Central Kalimantan also show comparable pattern where most of the districts in these provinces are clustered in Club 3, and mostly the districts in Maluku and Nusa Tenggara provinces dominate Club 4 and Club 5. More surprisingly, districts belonging to the same club also tend to be geographically close. To put it another way, the clubs seem to be spatially concentrated. This could indicate some spatial agglomeration effects (Martin and Ottaviano, 2001) driven by factors like spatial externalities or spillovers (Quah, 1996).

Second, the distribution of clubs is also related to the spatial distribution, implying the prolonged existence of classical regional

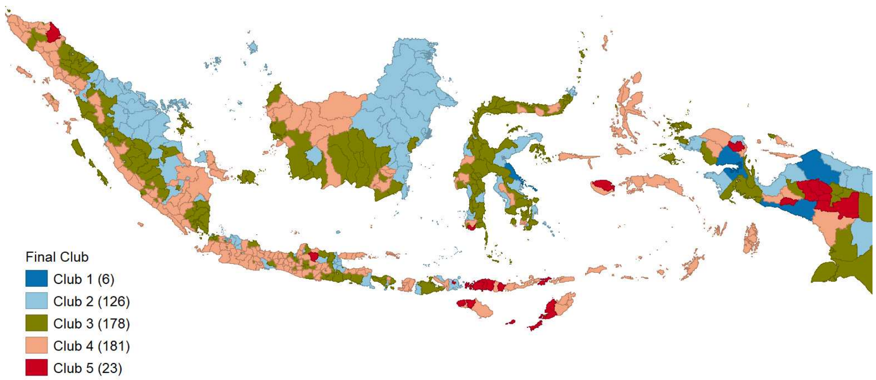


Figure 10: Spatial distribution of the convergence clubs

development problem in Indonesia; that is, the eastern regions of the archipelago are still lagged in development. It can be seen from the membership of the fifth club where out of 23 members, 21 districts are located in the eastern provinces of Indonesia, i.e., South Sulawesi, Nusa Tenggara, and Papua.

6.3 Policy implications

The difference in the progress of inter-regional development is natural. It is related to the variation in potential that each region has, both natural resources and geographical location. In addition, variation in the regional ability to manage their resources and potential are also factors that differentiate the success rate of development in each region. Despite the Indonesian economy's ability to maintain robust economic growth after the Asian financial crisis in 1997/98, the persistent income gap between regions still becomes one of major problems that could potentially be a source of a worse complication in the future. Not only could trigger social dispute stemmed from the perception of injustice among fellow communities, regional income inequality could also pose downside risks to the national economic growth.

To reduce regional income inequality, the Indonesian government needs to have a clear and accurate picture of regional imbalances among regions. In this context, the results of this study suggest that the growth path of income per capita among 514 Indonesian districts during the period of 2000-2017 does not converge to the same steady-state level. Similar to Kurniawan et al. (2019), this finding implies the absence of global convergence of income per capita among Indonesian regions. Instead, the growth process of Indonesian districts constitutes five local convergence clubs.

Interestingly, there is distinct characteristic across clubs, in particular between the highest income club (Club 1) and the lowest one (Club 5). At one end, Club 1 is dominated by regions with typical characteristics, i.e., big cities or natural resources-rich regions like Central Jakarta (the central district of the nation's capital city), Kediri (the largest national tobacco producer), Morowali (the location of recently developing nickel-based industrial park), Membramo Raya, Mimika and Teluk Bintuni (the natural resources-rich districts in the coastal area of Papua island, respectively). While at the other end, Club 5 predominantly consists of districts that have long been struggling with poverty issues. In addition, the income gap among these five clubs is also considerably large, suggesting that the potential regional development policies might be different across clubs. For example, the development policies for districts in Club 1 might be directed to seeking new sources of growth to avoid income stagnation. Meanwhile, the majority of districts in Club 2, 3, and 4 could focus their program on developing the middle-sized cities and more programs on improving connectivity. Differently, policies on basic infrastructures and public services provision should be implemented in districts of Club 5.

Furthermore, the spatial distribution of clubs can provide non-trivial information for inter-provincial policymaking to reduce income inequality. For example, Figure 10 shows that some districts in Club 5 share the border with districts in Club 1, implying the potential to further strengthen positive spillover from the rich districts to their poor neighboring districts. In Papua province, for instance, Pegunungan Arfak (Club 5) is the direct neighbor of Teluk Bintuni (Club 1); Deiyai, Puncak, and Nduga (Club 5) share the border with Mimika (Club 1); Puncak Jaya and Tolikara (Club 5) are the neighbors of Membramo Raya (Club 1). Among others, inter-provincial policies such as strengthening connectivity and promoting trade between these regions are highly favorable. The same fashion can also be applied in some poor districts of Club 5 such as Aceh Timur in Aceh province, Blora in Central Java province, and Jeneponto in South Sulawesi province.

Lastly, given the persistence of the west-east development gap observed in this study, the central government policies to support the development of physical infrastructures and basic public services provision in the eastern parts of the archipelago are strongly suggested to reduce regional income inequality.

7. Concluding remarks

A development process is sustainable when it favors social inclusion and the reduction of regional disparities. In this context, our study documents the evolution of disparities in income per capita among Indonesian districts after the implementation of decentralization policy. We use a novel district-level dataset that covers 514 Indonesian districts over the 2000-2017 period. From a methodological perspective, the convergence club test proposed by Phillips and Sul (2007) is applied to evaluate whether all districts converge to a common steady-state growth path.

The main findings are as follows. First, there is no overall convergence in income per capita among Indonesian districts after decentralizing. Instead, we find five convergence clubs that describe the evolution of income disparities across Indonesian districts. Consistent with previous literature, our results imply that income disparity across Indonesian districts remains a major problem even after implementing decentralization policies in the early 2000's. Second, we observe large and persistent differences between clubs, where the catching-up effects seem to exist only within clubs, but not between them. This pattern calls for differentiated development policies based on the composition of the clubs. Third, although districts belonging to the same province tend to converge to the same club, there is evidence that some provinces are composed of largely different districts, which belong to different clubs. Finally, the spatial distribution of convergence clubs clearly shows persistence in the east-west regional divide. In this context, the central government should coordinate regional policies to support the development in the eastern parts of Indonesia.

Based on the data construction and research methods of this paper, there are at least three avenues for further research. First, the comparability of regional data is crucial in the context of Indonesia, where the number of districts has largely increased over time. In this paper, we use a simple time-series interpolation method to construct a balanced panel dataset. As there is no unique and optimal interpolation method, further studies could apply other methods to re-evaluate the convergence clubs' composition. Second, alternative convergence analyses can be used to evaluate the composition and dynamics of the convergence clubs. In particular, distributional convergence methods could complement the club convergence approach used in this paper. Finally, recent studies about regional convergence emphasize the role of spatial spillovers in accelerating the convergence speed. Hence, formally integrating spatial spillovers into a club convergence framework is a promising direction for further research.

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Appendix A: Interpolating new districts data

During the decentralization, the number of districts in Indonesia increased significantly from 342 districts in 2000 to 514 districts in 2017. Due to this administrative proliferation, the sequential time series of GDP per capita at the constant price at the district level are difficult to obtain. Therefore, in this paper, we construct the balanced panel dataset for 514 districts level deflated by the constant price of 2010 from the Central Bureau of Statistics and INDODAPOER-World Bank. Specifically, we interpolated all missing values in both the regional GDP at constant price and the number of population. Also, we adjusted the historical data in some reference districts to avoid the structural break, i.e., the time series of reference districts before and after split-up.

Similar to Kurniawan et al. (2019), this paper uses a linear regression method with the reference district and (or) year as regressor(s) for the interpolation. We assumed that the new district is having co-movement with its reference district. The new districts' trend refers to their actual available data and follows its reference district (or year) when they are interpolated. For example, in Figure 11 we illustrate the comparison of GDP per capita of one of the proliferated districts, the Sungai Penuh City that became a new district in 2009 after separated from its origin district, the Regency of Kerinci.

In brief, our imputation/interpolation steps can be summarized as follows:

1. Constructing the reference district: The historical data of original district before split-up and the sum of the composite of new district(s) data after the proliferation are used as reference district.

2. Imputation and data adjustment: The time-series data of the original

district are adjusted by subtracting the reference district's time series data with the new district's imputed data before the proliferation year.

3. Constructing population data: The missing data of each district's total population are imputed using linear calculation of the population's share to the total province population.

4. Calculating regional GDP per capita: The per capita GDP at constant price for districts level is obtained by dividing GDP by each district's total population.

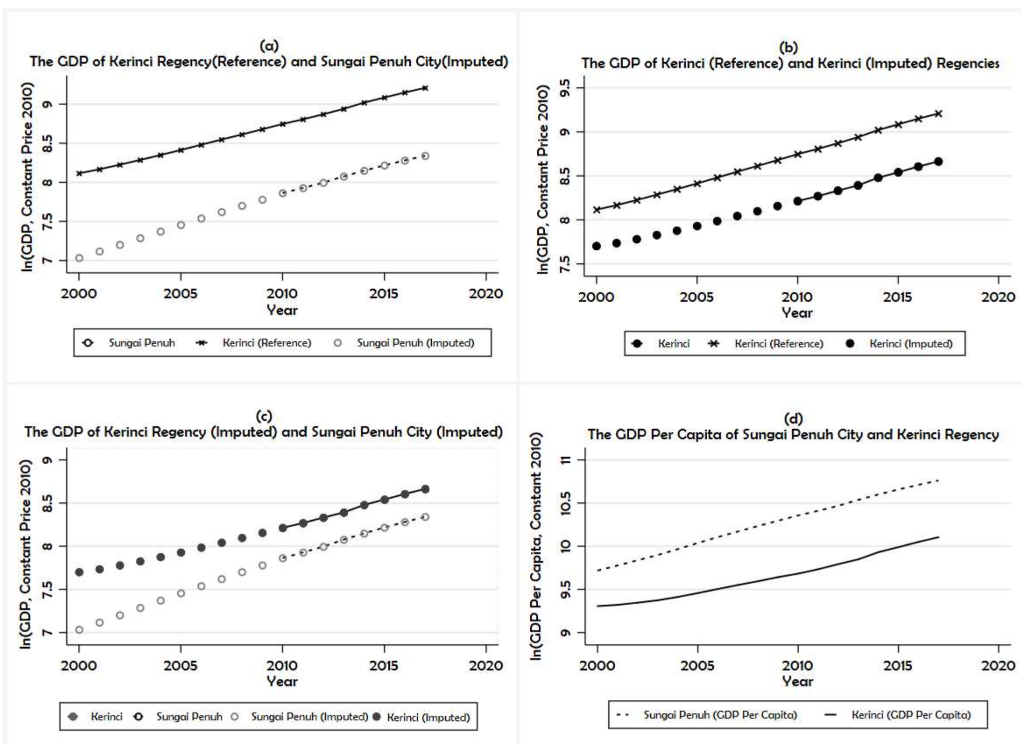

Figure 11: Comparison of imputed data and its reference

Appendix B: Club membership

Club 1 [6]: Jakarta Pusat, Kediri, Mamberamo Raya, Mimika, Morowali, Teluk Bintuni.

Club 2 [126]: Badung, Balangan, Balikpapan, Banda Aceh, Bandung, Banggai, Bangka Barat, Banyuwangi, Barito Utara, Batam, Batang Hari, Batu Bara, Bau-Bau, Bekasi, Bengkalis, Berau, Bima, Bintan, Bitung, Bojonegoro, Bontang, Boven Digoel, Bukittinggi, Bulungan, Buton Utara, Cilacap, Cilegon, Cirebon, Dumai, Fakfak, Gianyar, Gresik, Indragiri Hilir, Indragiri Hulu, Jakarta Barat, Jakarta Selatan, Jakarta Timur, Jakarta Utara, Jayapura, Jayapura, Kampar, Karawang, Karimun, Keerom, Kendari, Kepulauan Anambas, Kepulauan Meranti, Kepulauan Seribu, Kolaka, Kolaka Utara, Konawe Utara, Kota Baru, Kota Batu, Kuantan Singingi, Kudus, Kutai Barat, Kutai Kartanegara, Kutai Timur, Labuhan Batu, Labuhan Batu Selatan, Labuhan Batu Utara, Lamandau, Madiun, Magelang, Mahakam Ulu, Makassar, Malang, Malinau, Mamuju Utara, Manado, Manokwari, Maros, Medan, Mesuji, Minahasa Utara, Mojokerto, Mojokerto, Morowali Utara, Muara Enim, Murung Raya, Musi Banyuasin, Nabire, Natuna, Nunukan, Padang, Padang Panjang, Palembang, Palu, Pangkajene Kepulauan, Parepare, Pariaman, Pasir, Pasuruan, Pekanbaru, Pelalawan, Pematang Siantar, Pinrang, Purwakarta, Rokan Hilir, Salatiga, Samarinda, Sarmi, Sawahlunto, Semarang, Siak, Sibolga, Sidoarjo, Sorong, Sorong, Sumbawa Barat, Sungai Penuh, Surabaya, Surakarta, Tabalong, Tana Tidung, Tangerang, Tanjung Jabung Barat, Tanjung Jabung Timur, Tanjung Pinang, Tapanuli Selatan, Tarakan, Tegal, Wajo, Wakatobi, Waropen, Yogyakarta.

Club 3 [178]: Aceh Tengah, Agam, Asahan, Bandar Lampung, Banggai Kepulauan, Banggai Laut, Banjarmasin, Bantaeng, Banyumas, Barito Selatan, Barito Timur, Barru, Belitung, Belitung Timur, Bengkulu, Bengkulu Tengah, Binjai, Blitar, Blitar, Bogor, Bolaang Mongondow Selatan, Bolaang

Mongondow Timur, Bolaang Mongondow Utara, Bombana, Bone, Buleleng, Bulukumba, Bungo, Buol, Buton, Buton Selatan, Cimahi, Dairi, Deli Serdang, Denpasar, Dharmasraya, Donggala, Enrekang, Gorontalo, Gorontalo, Gorontalo Utara, Gunung Mas, Gunung Sitoli, Indramayu, Intan Jaya, Jambi, Jayawijaya, Jember, Jembrana, Jombang, Kaimana, Kapuas, Karanganyar, Karangasem, Karo, Katingan, Kendal, Kep.Siau Tagulandang Biaro, Kepulauan Mentawai, Kepulauan Sangihe, Kepulauan Selayar, Kerinci, Ketapang, Klungkung, Konawe, Konawe Kepulauan, Konawe Selatan, Kotawaringin Barat, Kotawaringin Timur, Kubu Raya, Kupang, Lahat, Lamongan, Lampung Selatan, Lampung Tengah, Lampung Timur, Lampung Utara, Langkat, Lhokseumawe, Limapuluh Kota, Lingga, Lumajang, Luwu, Luwu Timur, Luwu Utara, Magetan, Malang, Mamberamo Tengah, Mamuju, Mandailing Natal, Mappi, Mataram, Merangin, Merauke, Metro, Minahasa, Minahasa Selatan, Minahasa Tenggara, Muaro Jambi, Muna, Muna Barat, Musi Rawas, Musi Rawas Utara, Nagan Raya, Pacitan, Padang Lawas Utara, Padang Pariaman, Palangkaraya, Palopo, Pangkal Pinang, Parigi Moutong, Pasaman Barat, Pasuruan, Pati, Payakumbuh, Pegunungan Bintang, Penajam Paser Utara, Pesawaran, Pohuwato, Polewali Mandar, Pontianak, Poso, Prabumulih, Pringsewu, Probolinggo, Pulang Pisau, Raja Ampat, Rejang Lebong, Rokan Hulu, Sabang, Sambas, Samosir, Sarolangun, Semarang, Serang, Serang, Serdang Bedagai, Sidenreng Rappang, Sigi, Sijunjung, Simalungun, Singkawang, Sinjai, Sleman, Solok, Solok, Soppeng, Sorong Selatan, Sragen, Sukabumi, Sukamara, Sukoharjo, Sumbawa, Supiori, Tabanan, Takalar, Tana Toraja, Tanah Bumbu, Tanah Datar, Tanah Laut, Tangerang Selatan, Tanjung Balai, Tapin, Tasikmalaya, Tebing Tinggi, Tebo, Teluk Wondama, Ternate, Toba Samosir, Tojo Una-Una, Toli-Toli, Tomohon, Toraja Utara, Tuban, Tulang Bawang, Tulang Bawang Barat, Tulungagung, Yalimo.

Club 4 [181]: Aceh Barat, Aceh Barat Daya, Aceh Besar, Aceh Jaya, Aceh

Selatan, Aceh Singkil, Aceh Tamiang, Aceh Tenggara, Aceh Utara, Alor, Ambon, Asmat, Bandung, Bandung Barat, Bangka, Bangka Selatan, Bangka Tengah, Bangkalan, Bangli, Banjar, Banjar, Banjar Baru, Banjarnegara, Bantul, Banyuasin, Barito Kuala, Batang, Bekasi, Belu, Bener Meriah, Bengkayang, Bengkulu Selatan, Bengkulu Utara, Biak Numfor, Bireuen, Boalemo, Bogor, Bolaang Mongondow, Bondowoso, Bone Bolango, Boyolali, Brebes, Buru Selatan, Buton Tengah, Ciamis, Cianjur, Cirebon, Demak, Depok, Dogiyai, Dompu, Empat Lawang, Ende, Flores Timur, Garut, Gayo Lues, Gowa, Grobogan, Gunung Kidul, Halmahera Barat, Halmahera Selatan, Halmahera Tengah, Halmahera Timur, Halmahera Utara, Hulu Sungai Selatan, Hulu Sungai Tengah, Hulu Sungai Utara, Humbang Hasundutan, Jepara, Kapuas Hulu, Kaur, Kayong Utara, Kebumen, Kediri, Kepahiang, Kepulauan Aru, Kepulauan Sula, Kepulauan Talaud, Kepulauan Tidore, Kepulauan Yapen, Klaten, Kolaka Timur, Kotamobagu, Kulon Progo, Kuningan, Lampung Barat, Landak, Langsa, Lebak, Lebong, Lombok Barat, Lombok Tengah, Lombok Timur, Lombok Utara, Lubuklinggau, Madiun, Magelang, Majalengka, Majene, Malaka, Maluku Barat Daya, Maluku Tengah, Maluku Tenggara, Maluku Tenggara Barat, Mamasa, Mamuju Tengah, Manokwari Selatan, Maybrat, Melawi, Mempawah, Mukomuko, Ngada, Nganjuk, Ngawi, Nias, Nias Barat, Nias Selatan, Nias Utara, Ogan Ilir, Ogan Komering Ilir, Ogan Komering Ulu, Ogan Komering Ulu Selatan, Ogan Komering Ulu Timur, Padang Lawas, Padang Sidempuan, Pagar Alam, Pakpak Bharat, Pamekasan, Pandeglang, Pangandaran, Paniai, Pasaman, Pekalongan, Pekalongan, Pemalang, Penukal Abab Lematang Ilir, Pesisir Barat, Pesisir Selatan, Pidie, Pidie Jaya, Ponorogo, Probolinggo, Pulau Morotai, Pulau Taliabu, Purbalingga, Purworejo, Rembang, Sampang, Sanggau, Sekadau, Seluma, Seram Bagian Barat, Seram Bagian Timur, Seruyan, Sikka, Simeulue, Sintang, Situbondo, Solok Selatan, Subang, Subulussalam, Sukabumi, Sumba Barat, Sumba

Timur, Sumedang, Sumenep, Tambrauw, Tangerang, Tanggamus, Tapanuli Tengah, Tapanuli Utara, Tasikmalaya, Tegal, Temanggung, Timor Tengah Selatan, Timor Tengah Utara, Trenggalek, Tual, Way Kanan, Wonogiri, Wonosobo.

Club 5 [23]: Aceh Timur, Bima, Blora, Buru, Deiyai, Jeneponto, Kupang, Lanny Jaya, Lembata, Manggarai, Manggarai Barat, Manggarai Timur, Nagekeo, Nduga, Pegunungan Arfak, Puncak, Puncak Jaya, Rote Ndao, Sabu Raijua, Sumba Barat Daya, Sumba Tengah, Tolikara, Yahukimo.

Appendix C: Test for clubs merging

Phillips and Sul (2009) propose a merging test to evaluate whether the clubs identified according to the clustering algorithm described in Section 3.3 can be merged. Thus, we used a club merging algorithm by Phillips and Sul (2009) to test for merging between the adjacent clubs. The procedure works as follows:

1. The log t test is applied on the first two initial groups identified in the clustering mechanism described in Section 3.3. If the t-statistic is larger than -1.65, these two groups together form a new convergence club;

2. The log t test is repeated by adding the next club, and the process continues until the condition of t-statistic is larger than -1.65 is achieved;

3. If the convergence hypothesis is rejected, that is when t-statistic is larger than -1.65 does not hold, we assume that all previous groups converge, except the last added one. Hence, we restart the merging algorithm from the club for which the hypothesis of convergence does not hold.

Appendix D: Convergence test using a trend parameter of 400

Table 9: Global convergence test (trend parameter of 400)

	Coefficient	Standard Error	t-statistic
log(t)	-0.53	0.02	-23.02

Note: The null hypothesis of convergence is rejected when the t-statistic is less than -1.65.

Table 10: Local convergence test (trend parameter of 400)

	Club1	Club2	Club3	Club4	Club5	Club6
Coefficient	0.61	0.27	0.02	0.25	0.03	0.67
t-statistic	6.25	3.25	0.42	3.89	1.25	51.39
N. of regions	4	10	106	186	50	4

	Club7	Club8	Club9	Club10	Club11	Club12
Coefficient	2.43	1.81	1.33	0.81	2.54	0.00
t-statistic	9.48	8.73	11.84	11.88	8.24	-.07
N. of regions	24	70	10	24	4	22

Note: The null hypothesis of convergence is rejected when the t-statistic is less than -1.65.

Table 11: Merge test (trend parameter of 400)

	Club1+2	Club2+3	Club3+4	Club4+5	Club5+6	Club6+7
Coeff	0.30	-0.07	-0.24	0.02	0.08	2.25
T-stat	3.79	-1.49	-6.39	0.58	3.85	9.86

	Club7+8	Club8+9	Club9+10	Club10+11	Club11+12
Coeff	1.08	1.32	0.19	0.27	-0.16
T-stat	8.41	8.56	6.20	6.49	-6.05

Note: The null hypothesis of convergence is rejected when the t-statistic is less than -1.65.

Table 12: After-merge clubs (trend parameter of 400)

	Club1	Club2	Club3	Club4	Club5
Coeff	0.30	0.02	0.01	0.03	0.00
T-stat	3.79	0.42	0.41	0.71	-0.07
Size	14	106	240	132	22

Note: The null hypothesis of convergence is rejected when the t-statistic is less than -1.65.

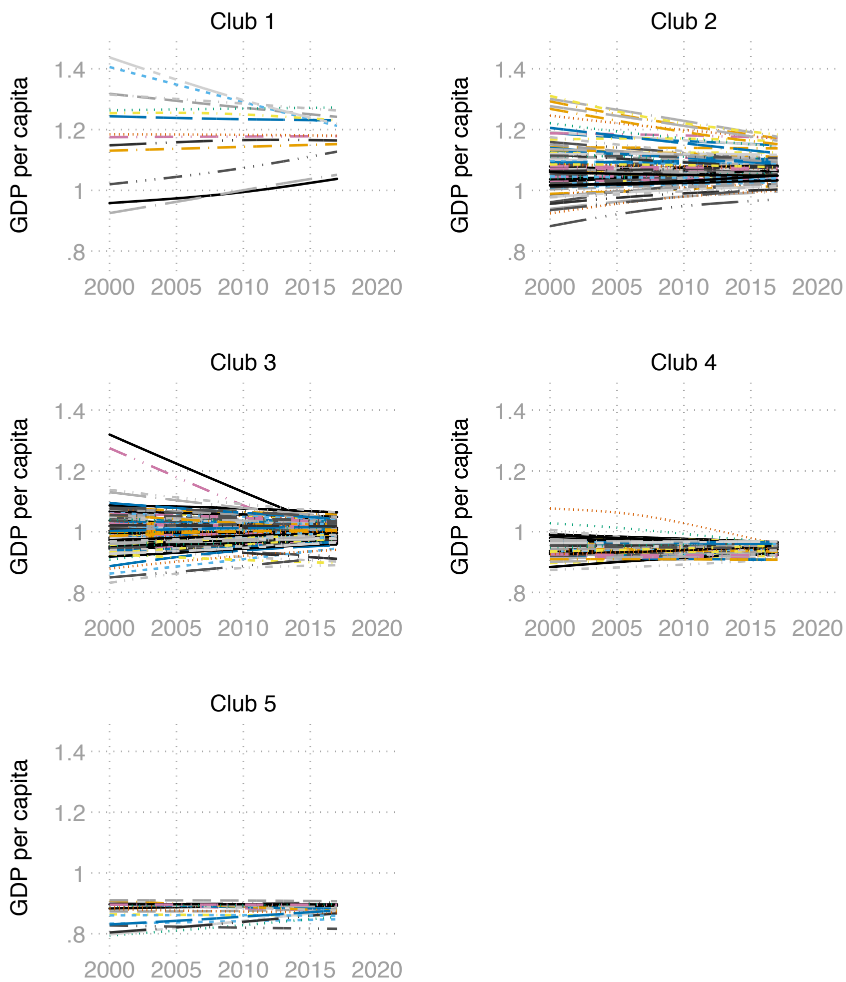

Figure 12: Convergence clubs and transition paths (trend parameter of 400)

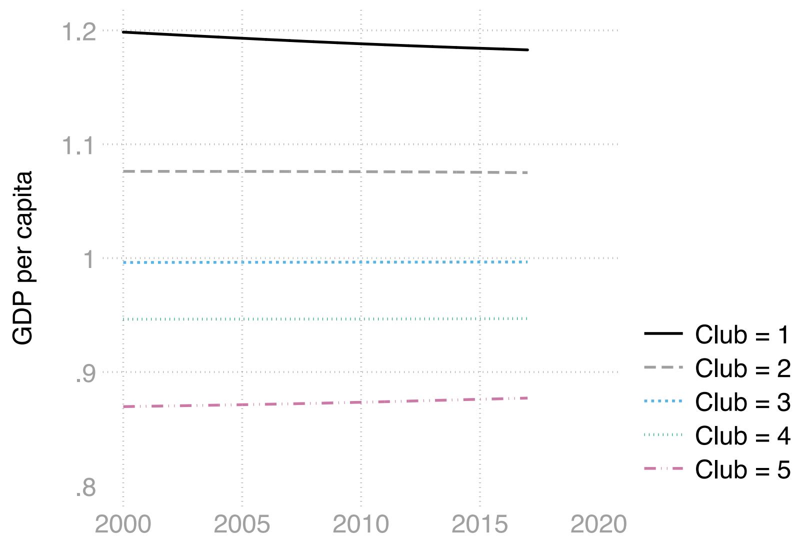

Figure 13: Convergence clubs trends (trend parameter of 400)

Appendix E: Classical convergence analysis for a sample of 342 districts

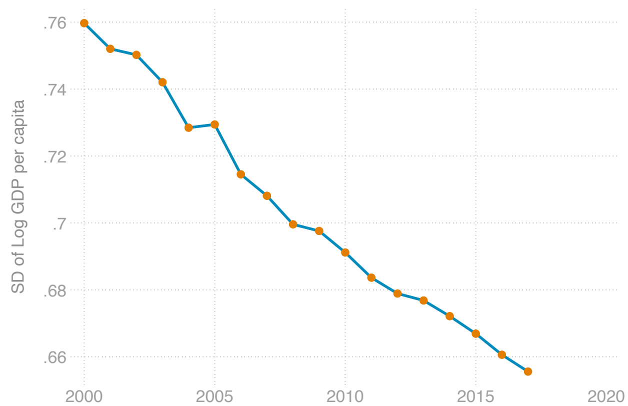

Figure 14: Sigma convergence across 342 districts

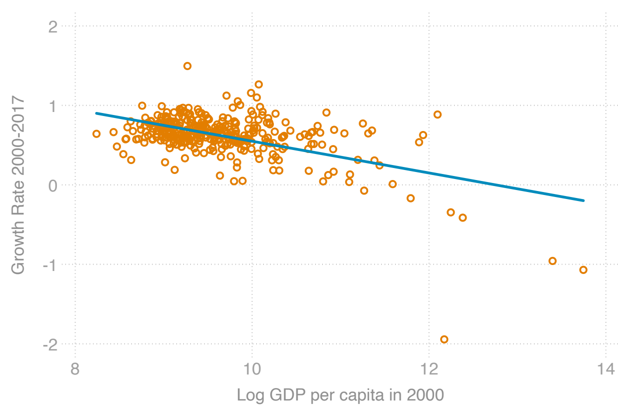

Figure 15: Beta convergence across 342 districts