Regional Efficiency Dispersion, Convergence, and Efficiency Clusters: Evidence from the Provinces of Indonesia 1990-2010

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11 September 2019

Regional Efficiency Dispersion, Convergence, and Efficiency Clusters: Evidence from the Provinces of Indonesia 1990-2010

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(Preliminary Version 1.0)

Abstract

This paper studies efficiency convergence across provinces in Indonesia over the 1990-2010 period. Through the lens of both classical and distributional convergence frameworks, the dispersion dynamics of pure technical efficiency and scale efficiency are contrasted. The results suggest that—on average—there is regional convergence in both measures of efficiency. However, results from the distributional framework indicate the existence of two separate convergence clusters within the pure technical efficiency distribution. Thus, since scale efficiency is characterized by only one convergence cluster, the two clusters of pure technical efficiency appear to be driving the overall efficiency dynamics of Indonesia.

Keywords:

Efficiency, Convergence, Distribution-based clustering, Nonparametric distribution, Indonesia

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* I am grateful to all participants of the Economic Development Policy and Management seminar at Nagoya University for the insightful comments and suggestions.
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1 Introduction

Large per-capita income differences across provinces is a well known issue of the Indonesian economy (Esmara, 1975). Regional income differences seem to persist despite considerable policy efforts that aim to promote a more balanced growth path. Although a series of five-year development plans, fiscal transfer programs, internal migration policies, and integrated economic zones initiatives aimed to reduce regional disparities, the outcomes still remain below their original targets (Akita, 1988; Garcia and Soelistianingsih 1998; Kataoka, 2012).

In the economic growth literature, per-capita income differences are commonly accounted for by two proximate sources: the accumulation of factor inputs and the efficiency with which those inputs are used (Caselli, 2005). Factor inputs typically include measures of both physical capital and human capital. Efficiency, on the other hand, can be further decomposed into different types of efficiencies. The Data Envelopment Analysis (DEA) framework of Charnes et al. (1978), for instance, decomposes overall efficiency into pure technical efficiency and scale efficiency.

Both the accumulation of factor inputs and the efficiency with which they are used are two key sources for understanding the large income differences across the Indonesian provinces. However, as noted by Kataoka (2018), relatively few studies have examined the role of efficiency in determining regional income disparities in Indonesia. The work of Kataoka (2018) is one those studies; by estimating the three measures of efficiency of the DEA framework, the results of his study indicate that efficiency differences across provinces have decreased over the 1990-2010 period. In other words, provinces in Indonesia have tended to converge in terms of their relative efficiency levels.

In an attempt to contribute and extend the convergence findings of Kataoka (2018), this paper studies the dynamics of regional efficiency disparities through the lens of both the classical convergence approach of Barro and Sala-i-Martin (1992) and the distributional convergence approach of Quah (1997). Results from the classical approach suggest that—on average—there is regional convergence in the three measures of efficiency of the DEA framework. Results from the distributional approach, which emphasizes tendencies beyond average behavior, suggest that there are two separate clusters of convergence in overall efficiency (OE) and in pure technical efficiency (PE). In contrast, scale efficiency (SE) is the only variable where the Indonesian provinces appear to be converging to a unique equilibrium. These results imply that the overall dynamics of efficiency appear to be mostly driven by the dynamics of pure technical efficiency and not necessarily scale efficiency.

From a methodological standpoint, the contribution of this paper is two fold. First, it extends and complements the original framework of Quah (1997) by integrating the distribution-based clustering algorithm of Menardi and Azzalini (2014). Second, it applies the conditional density estimator of Hyndman et. al (1996), which is shown to have better statistical properties than the original estimator of Quah (1997).

The rest of this paper is organized as follows. Section 2 describes the data and the empirical frameworks. Section 3 presents the results of both classical and distributional convergence analyses. Finally, Section 4 offers some concluding remarks and points out some avenues for further research.

2 Data and Methods

2.1 Efficiency Measurements and Data

This paper uses efficiency data for 26 contiguous provinces of Indonesia over the 1990-2010 period. More specifically, the data is from the recent work of Kataoka (2018). In this paper, this author uses the Data Envelope Analysis (DEA) framework to quantify the relative efficiency with which inputs are used to produce output at the provincial level in Indonesia. Provincial output is measured by the Gross Regional Domestic Product, and inputs include both measures of human capital (labor force adjusted by educational attainment) and physical capital (measured in in monetary units).

DEA is a nonparametric framework that is used to measure the relative efficiency of decision-making units (Charnes et al., 1978). Originally, this framework has been mainly used for micro-level production units[1]. However,

[1]The DEA literature usually refers to this production units as decision-making units (DMUs). They are responsible for turning inputs into output(s). Note that for the purposes

this framework has become increasingly more popular for the analysis of meso-level production units, such as cities, districts, and provinces (Charnes et al., 1989; Halkos and Tzeremes, 2010; Schaffer et al., 2011) .

One particularly appealing feature of the DEA framework is that the measured overall efficiency (OE) can be further decomposed into pure technical efficiency (PE) and scale efficiency (SE). Equation 1 summarizes this decomposition:

$$\text{Overall efficiency} = \text{Pure efficiency} * \text{Scale efficiency}. \tag{1}$$

At a basic level, pure (technical) efficiency refers to the managerial capability of using inputs and scale efficiency refers to the exploitation of economies of scale by operating at an optimal size. Kataoka (2018, Table 2) provides estimates for these three efficiency measurements for a sample of 26 Indonesian provinces over the 1990-2010 period.

2.2 Classical Convergence Framework

2.2.1 Beta Convergence

The classical convergence framework of Barro and Sala-i-Martin (1991,1992) for testing the income convergence the macro level has been increasingly applied to the regional-level context (Magrini, 2004). It has also been applied to other variables beyond income. In this framework, the growth rate of a variable, g_y, is a function of its initial level in log terms, $log(y_0)$. If, in a regression setting, there is an inverse relationship between these two variables, then a process of regional convergence is taking place. This notion of convergence is commonly referred as beta convergence in the economic growth literature. In the context of the current paper, the existence of beta convergence would indicate that the less efficient provinces of Indonesia are catching up with most efficient ones.

For econometric estimation purposes, Barro and Sala-i-Martin (1991,1992) suggest the following specification for studying convergence across the regions of a country:

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of the current paper, the terms decision-making units and production units are used interchangeably.

$$g_y = \gamma - \frac{\left(1 - e^{-\beta t}\right)}{t} \, log \, y_0 + u_t, \tag{2}$$

where g_y is the average growth rate of the variable y, γ is a constant, t is a time index, β is the speed of convergence, y_0 is the initial level of the variable, and u_t is a random disturbance. After estimating the speed of convergence, β, a second parameter of interest, known as the "half-life" measure of convergence, can be computed as:

$$half\text{-}life = \frac{log2}{\beta}. \tag{3}$$

This measure indicates the time (usually measured in years) that the average region would need to halve the distance between its initial efficiency level and its final convergence equilibrium.

2.2.2 Sigma Convergence

There is also a much more general notion of convergence, which is known as sigma convergence. This type of convergence refers to the secular decrease in the cross-regional dispersion of a variable over time. The cross-regional dispersion is then typically measured by the standard deviation of the logarithm of a variable at different time periods. For the purposes of the current paper, the cross-regional dispersion, σ_t, is measured as follows:

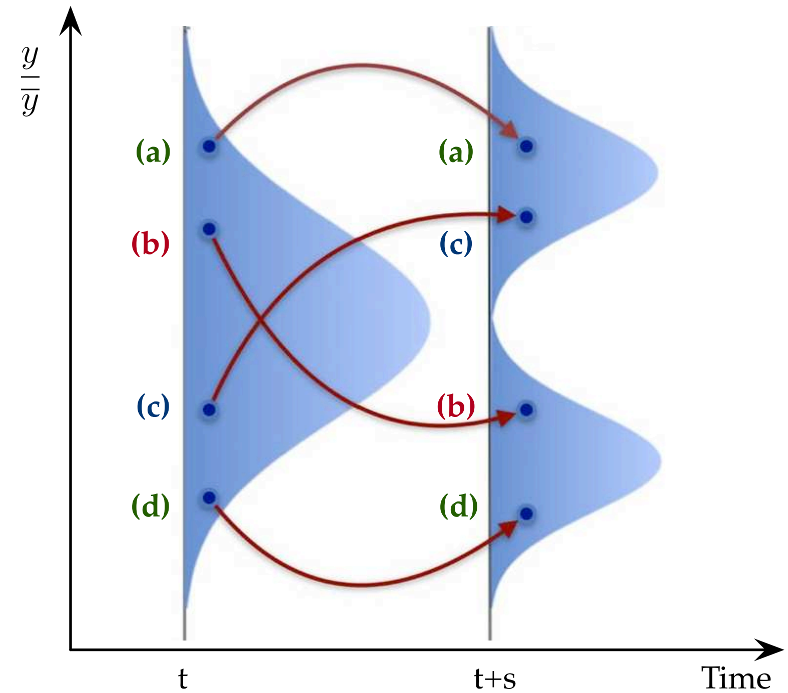
$$\sigma_t = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N} \left(log\left(y_{i,t}\right) - \overline{log(y_t)}\right)^2}, \tag{4}$$

where N is the number of regions (provinces) in the sample, $y_{i,t}$ is the efficiency score of region i at time t, and $\overline{log(y_t)}$ is the average of the natural logarithm of efficiency at time t.

2.3 Distributional Convergence Framework

The classical convergence framework is sometimes criticized by its excess focus on average behavior and the existence of a unique convergence equilibrium. It ignores possible heterogenous patterns of convergence and the formation of local convergence clusters. Motivated by these limitations, Quah (1993; 1996;

***Figure 1*. Distribution dynamics framework: A graphical summary**



Note: $y/\bar{y}$ indicates that the value of the variable y is expressed in relative terms. $\bar{y}$ indicates the convergence benchmark or the sample average.
Source: Adapted from Quah (1993).

1997) introduced the distributional convergence approach. In contrast to the classical framework, the distributional framework focuses on the dynamics of the entire cross-sectional distribution.[2]

Figure 1 shows a graphical summary of the distributional convergence framework. Two essential features should be noted. First, the external-shape dynamics of the distribution indicate the formation of two local convergence clusters. Second, the intra-distributional dynamics indicate the sources of the clustering process. For instance, some regions (such as a and d) may show large and persistent differences over time. Others (such as c), may move forward and catch-up with the upper cluster. And others (such as b), may move backward and catch-down with the bottom cluster.

To formalize the intuition of Figure 1 in the context of the variables of the

[2]See Epstein et al. (2003), Magrini (1999; 2004), Bianco (2016) or Mendez-Guerra (2018) for more comprehensive presentations of the distributional convergence framework

current paper, let us first define $f_t(x)$ as the cross-regional efficiency distribution at time t and $f_{t+s}(y)$ as the distribution at time $t+s$. Next, the evolution from time t to time $t+s$ is commonly modeled as a first-order autoregressive process of a time-homogeneous Markov chain. That is,

$$\underbrace{f_{t+s}(y)}_{Future\ Distribution} = \int \underbrace{f_{t+s|Z_t=x}}_{Stochastic\ Kernel} \underbrace{f_t(x)}_{Initial\ Distribution} dx, \tag{5}$$

where the transformation of the initial distribution, $f_t(x)$, into the future distribution, $f_{t+s}(y)$, depends on the stochastic kernel, $f_{t+s|Z_t=x}(x)$, which is a transitional operator commonly estimated as a conditional distribution function. That is,

$$f_{t+s|Z_t=x}(\mathsf{x}) = \frac{f_{t,t+s}(y,x)}{f_t(x)}, \tag{6}$$

where $f_{t,t+s}(y,x)$ is an unconditional joint distribution and $f_t(x)$ is the marginal distribution of x. Lastly, let us define the unconditional joint distribution as:

$$f_{t,t+s}(y,x) = \frac{1}{nh_z h_x} \sum_{i=1}^{n} K_z\left(\frac{z-z_i}{h_z}\right) K_x\left(\frac{x-x_i}{h_x}\right), \tag{7}$$

where K_y and K_x denote Gaussian kernel functions, and h_z and h_x denote kernel bandwidths for y and x, respectively.[3]

The stochastic kernel provides valuable information about intra-distributional dynamics and the formation of local convergence clusters. As shown in Equation 6, it depends on two components: the unconditional joint distribution, $f_{t,t+s}(y,x)$, and the initial marginal distribution, $f_t(x)$. To evaluate the effect of the former, we will follow the approach of Azzalini et. al (2007) and Menardi and Azzalini (2014). To evaluate the effect of the latter, we will follow the approach of Hyndman et. al (1996).

[3]Optimal flexible bandwidhts are derived from the the minimization of the asymptotic mean integrated square error (AMISE).

3 Results and Discussion

3.1 Classical Convergence

Table 1 presents the results of the beta convergence framework. The overall finding is that the less efficient provinces are catching up with the most efficient ones. This convergence process is statistically significant, consistent across the three efficiency scores, and considerably fast. In particular, convergence in pure (technical) efficiency (PE) appears to be the fastest. In this score, the provinces of Indonesia are expected to halve its efficiency differences in the next 5.6 years. Interestingly, the speed of convergence of both pure efficiency (PE) and scale efficiency (SE) appears to be very similar.

Table 1
Beta convergence across Indonesian Provinces

	Dependent Variable		
	Growth of Overall Efficiency (OE) (1990-2010)	Growth of Pure Efficiency (PE) (1990-2010)	Growth of Scale Efficiency (SE) (1990-2010)
Beta coefficient	- 0.84	-0.91	- 0.91
Speed of convergence	0.09	0.12	0.12
Half-life time (in years)	7.6	5.6	5.7
R-squared	0.84	0.89	0.82
P-value of beta	0.00	0.00	0.00

Note: All regressions include a constant term, which is not presented in the table.
Source: Author's calculations using data from Kataoka (2018).

Table 2 presents the results of the sigma convergence framework. Consistent with the beta-convergence finding, there is a reduction in the efficiency dispersion over time. This process is both statistically significant and consistent across the three efficiency scores. When contrasting the dispersion reduction in pure efficiency with that of scale efficiency, the former shows a larger absolute change. Thus, pure efficiency accounts for more of the variation in overall efficiency.

Table 2
Sigma convergence across Indonesian Provinces

	Overall Efficiency (OE)	Pure Efficiency (PE)	Scale Efficiency (SE)
Dispersion in 1990	0.63	0.54	0.46
Dispersion in 2010	0.25	0.18	0.20
Dispersion Ratio $\left(\frac{\sigma_{1990}}{\sigma_{2010}}\right)$	2.53	3.03	2.31
F-Statistic	6.40	9.20	5.30
P-value	0.00	0.00	0.00

Note: Following the convention of the literature, the dispersion is measured by the standard deviation of the natural logarithm of each variable.
Source: Author's calculations using data from Kataoka (2018).

3.2 Distributional Convergence

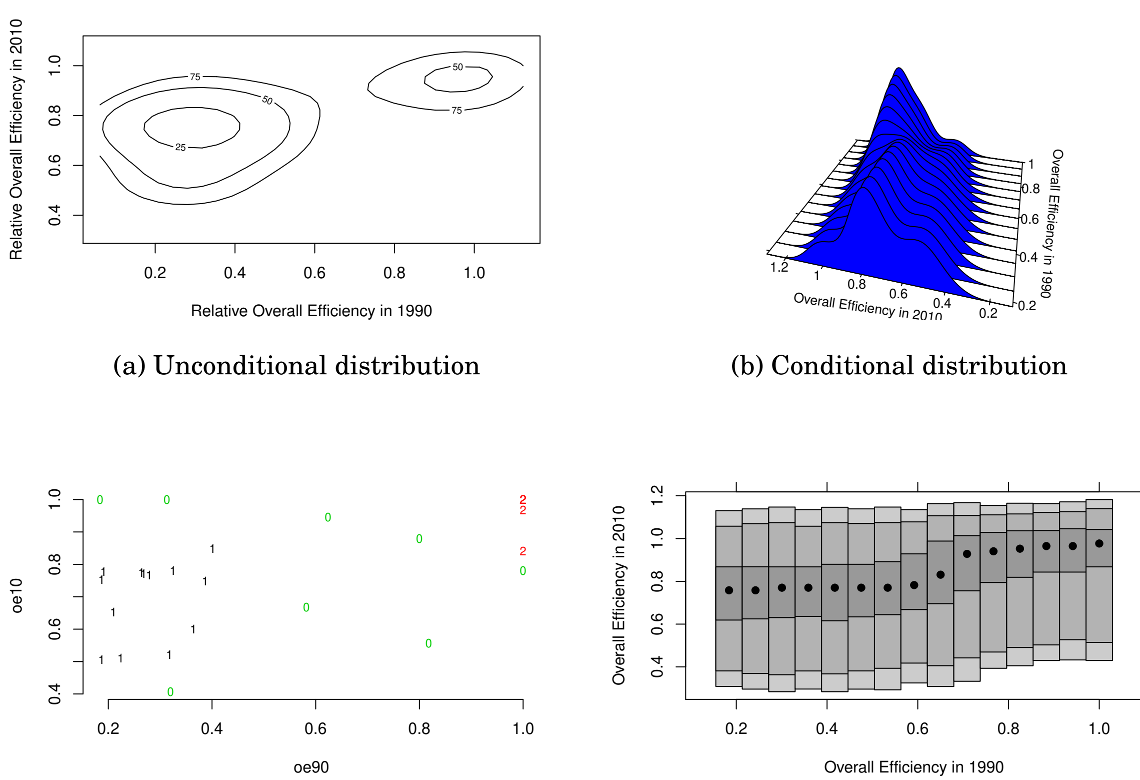
3.2.1 Overall Efficiency

Figure 2 shows the distributional convergence results for the overall efficiency score (OE). As shown in Panel (a), the most noticeable feature of the regional dynamics is the existence of two separate clusters. A relatively small and high-efficiency cluster is located at around 1 in each year. The regions belonging to this cluster are those high-efficiency provinces of 1990 that remained highly efficient in 2010. A relatively large and low-efficiency cluster is located at around 0.8 of the efficiency score of 2010. The regions belonging to this cluster used to have an efficiency score below 0.6 in 1990. By the year 2010, however, they largely improved relative to their initial position and started process of convergence both among themselves and with the regions of the efficiency frontier. However, this second convergence process is not yet complete and there remains a significant distance between the high-efficiency cluster and the low-efficiency one.

Based on the clustering framework of Azzalini and Torelli (2007), Panel (c) refines the cluster composition by identifying the "core" members in each cluster. Through the lens of this framework, regions are further classified into

3 groups: the core cluster 1, conformed by the low-efficiency regions; the core cluster 2, conformed by the high-efficiency regions; and a remaining group of transitional outliers (marked with the number 0). This latter group is mostly composed by those regions that drastically changed their relative position between the 1990-2010 period.

***Figure 2*. Distributional convergence and clusters in overall efficiency**



(a) Unconditional distribution

(b) Conditional distribution

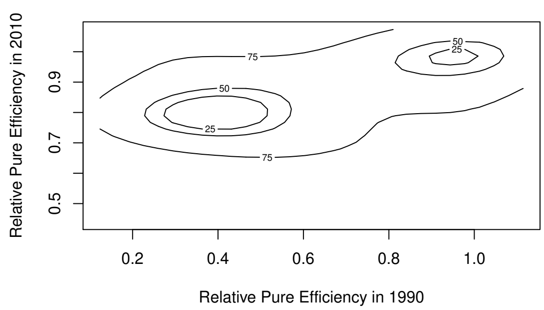
(c) Distribution-based clusters

(d) Conditional distribution: Modal boxplots

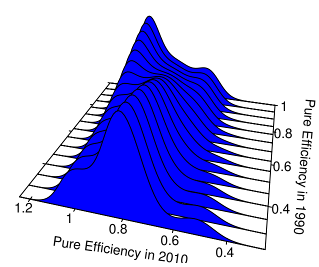
Notes: Panel A: The uncondtional bivarate distribution is estimated using the nonparametric methods described in Menardi and Azzalini (2014). Panel B: The uncondtional bivarate distribution is estimated using the nonparametric methods described in Hyndman et. al (1996). Panel C: The distribution-based clusters are indentified using algorithm of Menardi and Azzalini (2014). Panel D: The modal boxplots are also described in Hyndman et. al (1996). Darker-shaded stripes indicate higher density areas, and the mode for each conditional density is shown as a bullet point.
Source: Author's calculations using data from Kataoka (2018).

Based on the distributional convergence framework of Quah (1996; 1997) and the stochastic kernel estimator of Hyndman, Bashtannyk and Grunwald (1996), Panels (b) and (d) show evolution of the efficiency distribution conditional on its initial level in 1990. On the one hand, the regions with an efficiency score between 0.2 and 0.6 in 1990 tended to convergence to an efficiency score of 0.8 in 2010. On the other, regions with an efficiency score between 0.7 and 1 in 1990 tended to convergence to an efficiency score just under 1 in 2010. These results are consistent with those of Panels (a) and (c) in the sense that the dynamics of the overall efficiency distribution suggest the formation of two different convergence clubs.

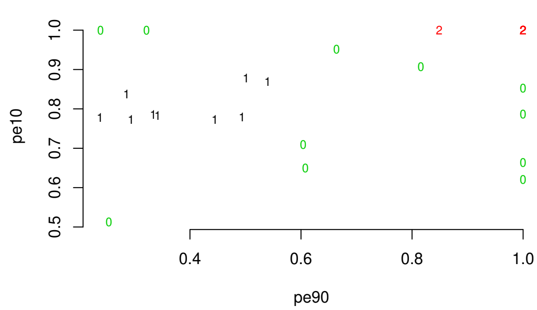
***Figure 3*. Distributional convergence and clusters in pure efficiency**



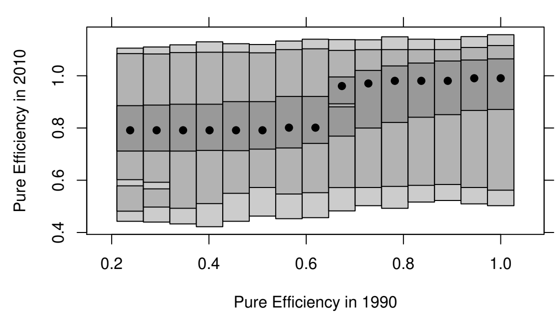
(a) Unconditional distribution



(b) Conditional distribution



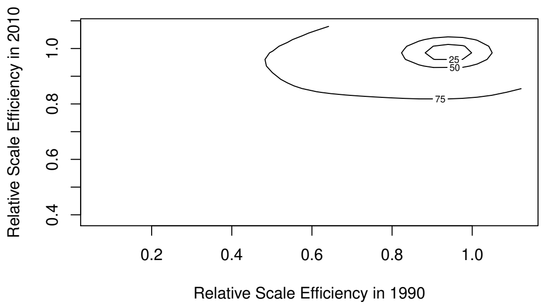
(c) Distribution-based clusters



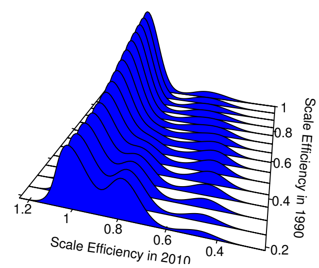
(d) Conditional distribution: Modal boxplots

Notes: Panel A: The uncondtional bivarate distribution is estimated using the nonparametric methods described in Menardi and Azzalini (2014). Panel B: The uncondtional bivarate distribution is estimated using the nonparametric methods described in Hyndman et. al (1996). Panel C: The distribution-based clusters are indentified using algorithm of Menardi and Azzalini (2014). Panel D: The modal boxplots are also described in Hyndman et. al (1996). Darker-shaded stripes indicate higher density areas, and the mode for each conditional density is shown as a bullet point.
Source: Author's calculations using data from Kataoka (2018).

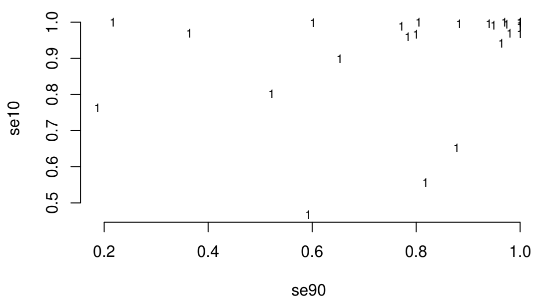
Figure 4. Distributional convergence and clusters in scale efficiency



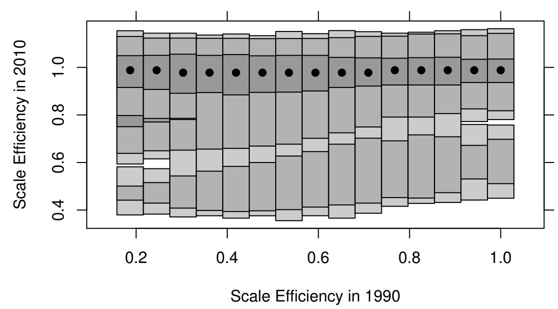
(a) Unconditional distribution



(b) Conditional distribution



(c) Distribution-based clusters



(d) Conditional distribution: Modal boxplots

Notes: Panel A: The uncondtional bivarate distribution is estimated using the nonparametric methods described in Menardi and Azzalini (2014). Panel B: The uncondtional bivarate distribution is estimated using the nonparametric methods described in Hyndman et. al (1996). Panel C: The distribution-based clusters are indentified using algorithm of Menardi and Azzalini (2014). Panel D: The modal boxplots are also described in Hyndman et. al (1996). Darker-shaded stripes indicate higher density areas, and the mode for each conditional density is shown as a bullet point.
Source: Author's calculations using data from Kataoka (2018).

3.2.2 Pure (Technical) Efficiency vs Scale Efficiency

Figure 3 and Figure 4 show the distributional convergence results for the two sources of overall efficiency (OE): pure technical)efficiency (PE) and scale efficiency (SE). On the one hand, the convergence dynamics of PE are largely similar to those of OE. First, the unconditional distribution shows two separate clusters (Panel a). A relatively small and high-efficiency cluster is located at around 1 and a relatively large and low-efficiency cluster is located at around 0.8 of the efficiency score of 2010. Next, the distribution-based clustering algorithm of Azzalini and Torelli (2007), indicates the existence of two core clusters and a group of transitional outliers (Panel c). Finally, the conditional distribution approach of Quah (1996; 1997) suggests that the regions with an efficiency score between 0.2 and 0.6 in 1990 tended to convergence to an efficiency score of 0.8 in 2010 and the regions with an efficiency score between 0.7 and 1 in 1990 tended to convergence to an efficiency score just under 1 in 2010. Taken together, all these results suggest that the convergence dynamics of PE tend to mirror those of the OE.

On the other hand, the dynamics of SE are largely different from those of OE (Figure 4). There is only one cluster of regions with no transitional outliers (Panel a and c). Furthermore, the conditional distribution (Panel b and d) indicates that most regions tended to converge towards the efficiency frontier. Thus, taken together, these results suggest that, at least in terms of scale efficiency, the provinces of Indonesia have been converging towards a unique equilibrium.

4 Concluding Remarks

Large and persistent per-capita income differences exist across the provinces of Indonesia. Standard economic growth theory suggests that, in a proximate sense, those differences can be driven by differences in capital accumulation and efficiency. Few studies about Indonesia have evaluated the potential role of efficiency. Among them, Kataoka (2018) finds that differences in overall efficiency and its two determinants (pure technical efficiency and scale efficiency) have decreased over the 1990-2010 period.

In this context, this paper evaluates the evolution of provincial efficiency differences through the lens of both the classical convergence approach of Barro and Sala-i-Martin (1992) and the distributional convergence approach of Quah (1997). Results from the classical approach support the previous finding of Kataoka (2018). That is,—on average—there is regional convergence in the three measures of efficiency. However, results from the distributional approach suggest significant heterogeneous patterns of convergence, which go beyond the performance of the average province. In particular, results suggest the existence of two local convergence clusters in both overall efficiency and pure technical efficiency. Scale efficiency is the only variable where the Indonesian provinces appear to be converging to a unique equilibrium. Taken together, these results imply that in order to reduce even further the overall efficiency differences across provinces, additional policy efforts should aim to reduce the distance between the two clusters of pure technical efficiency.

Finally, further research on efficiency convergence in Indonesia seems promising in at least Three immediate fronts. First, the robustness of the classical convergence analysis could be tested even further. For instance, Cole and Neumayer (2003) show that the results of beta convergence (or divergence) could be reversed when sample weights are added to the analysis. For Indonesia, those weights could be the number of districts, industries, or firms of each province. In the case of the sigma convergence analysis, Dalgaard (2001) and Ram (2018) show that different measures of dispersion, such as the coefficient of variation, could indicate not only different magnitudes of convergence, but also a different convergence direction. In other words, the dispersion dynamics identified by the coefficient of variation could contradict those of the standard deviation. Second, the distribution dynamics analysis could be extended and include an evaluation of convergence of the long-run (ergodic) distribution. The continuous state space approach of Johnson (2005) may prove useful for this endeavor. Finally, alternative clustering frameworks could be considered. Of particular relevance are those that identify clusters based on probability distribution functions. Among them, the finite mixture approach of Pittau and Zelli (2016) is a recent alternative that could be helpful for evaluating the robustness of the convergence clusters.

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