Regional Income Disparities, Distributional Convergence, and Spatial Effects: Evidence from Indonesia

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Abstract Using a novel dataset, this paper studies the spatio-temporal dynamics of income per capita across provinces and districts in Indonesia over the 2000-2017 period. First, an exploratory spatial analysis suggests that spatial autocorrelation is only significant at the district level and it appears to be robust from 2013 to 2017. Thus, at the district level, we proceed to use a spatial filtering model for decomposing income into a spatially independent component and a spatial residual. Next, through the lens of a distributional convergence framework, we find that the non-filtered income is characterized by a lack of regional mobility. In contrast, the spatially independent component shows a pattern of polarization. We conclude arguing that neighbor effects have played a significant role in reducing regional polarization in Indonesia.

Keywords Getis filter · Convergence · Distribution-based clustering · Nonparametric distribution · Indonesia

JEL Classifications O40 · O47 · R10 · R11

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1 Introduction

The decentralized system has replaced centralized governance in Indonesia for almost two decades. Through a greater political power and authority in fiscal and local administration, a decentralized system was expected to improve public service delivery and economic performance of the regions. However, research about decentralization in Indonesia has not provided a conclusive answer on the regional income effects of decentralization.

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).

This paper investigates the Gross Regional Domestic Product Per Capita (GRDPPC) convergence process at province and district levels during 2000-2017. Using a distributional convergence framework, spatial autocorrelation analysis, and the Getis filter, this study examines the regional dynamics of income and evaluates the spatial dependence across 34 provinces and across 514 districts.

Our findings show that spatial autocorrelation is only significant at the district level. By comparing the dynamics of filtered and non-filtered data, this study also shows that there is a lack of regional income mobility. In particular, spatial effects have induced the a more uniform progress at the tails of the regional income distribution. From a policy standpoint, the results imply that the policies and capabilities of local governments to support income distribution programs remain ineffective. Therefore, the role of the central government in reducing inequality, mainly through affirmative policies to poor regions, is still needed.

There are two major contributions of this research. First we utilize a novel database created for this work that includes all provinces and districts. Second, similar studies can be found for the economic development of regions and sub-regions in Europe such as Fischer and Stumpner (2010), in Brazil Cravo and Resende (2013) or in China Villaverde and Maza (2012). However, to the best of our knowledge, this is the first paper that studies the spatial filtering of income per capita for regions in Indonesia after the decentralization of the government.

The rest of the paper is organized as follows. Section 2 presents the methods and data. Section 3 shows the results of the the distributional convergence framework and the spatial approach including the spatial filtering of the data. Lastly, section 4 presents some concluding remarks.

2 Data and Methods

2.1 Data

After implementing the decentralization system, the number of provinces and districts in Indonesia have changed rapidly. The number of Provinces increased from 26 to 34 Provinces during 1999-2017, while the number of districts (regencies and cities) increased from around 330 districts to around 514 districts. Indonesia Central Bureau of Statistics has published periodically Gross Regional Domestic Product (GRDP) data by regencies in Indonesia since 1998. However, the number of regencies published has changing during the period of publication. In order to obtain a balanced panel dataset, this study constructs Gross Domestic Product Per Capita using data from Indonesia Database for Policy and Economic Research (INDODAPOER) World Bank.

We construct data for Per Capita GRPD from GRDP at constant price and population numbers by districts. The data has been updated from constant price 2000 to 2010 and the missing observation caused by creation of new districts are solved using interpolation. This study uses a linear regression method with year and reference provinces as regressors to do the interpolation. We assume that the new district is having co-movement with its reference district. The trend of the new districts refers to their actual data in the years when the data are available and follow its reference district in the year when they are interpolated.

Considering the geographical condition of Indonesia which is a country characterized by islands, int he case of provinces this study uses a distance parameter for the specification of neighboring districts for calculating the spatial weighted matrix and a queen contiguity criteria in the case of Districts. The Thiessen polygons needed to evaluate contiguity are centroids of districts. The centroid coordinates are determined on the capital city of the districts based on the data from Ministry of Internal Affairs and Geospatial Information Agency.

2.2 The Distributional Convergence framework

The study of the classical convergence hypothesis pioneered by Barro and Sala-i-Martin (Barro and Sala-i Martin (1991, 1992); Barro (1991)) is useful for analysing the average long-run development of regions. However, in order to study the internal dynamics of the cross-section, a novel approach was suggested by Quah (1993, 1996, 1997). This approach characterizes the dynamics of a system which is modeled using an stochastic kernel.

Figure 1 depicts a visual summary of the distributional dynamics framework. Utilizing stochastic kernels, the cross-sectional distribution and the internal dynamics of regions that are represented by a, b ,c and d in Figure 1 can be analysed. To formalize the framework shown in Figure 1, let us first define $Z_t(x)$ as the cross-regional GRDPPC distribution at time t and $Z_{t+s}(y)$ as the distribution at time $t+s$. The internal dynamics of the distribution are computed by evaluating the first-order

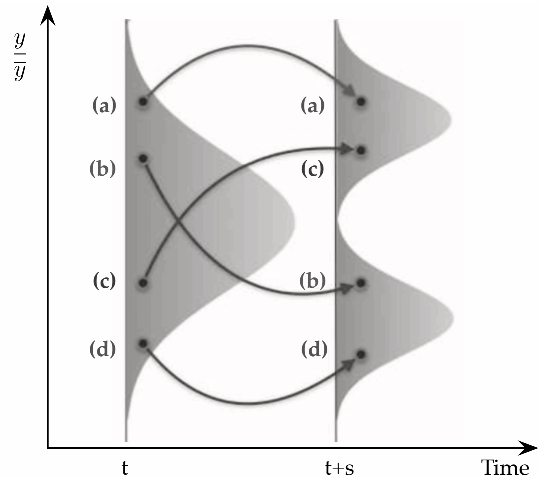


Fig. 1: Distribution dynamics framework: A graphical summary

Source: Adapted from Quah (1993).

auto-regressive process of a time-homogeneous Markov chain shown in equation (1)

$$\underbrace{z_{t+s}(y)}_{Future\,Distribution} = \int \underbrace{z_{t+s|Z_t=x}(y)}_{Stochastic\,Kernel} \underbrace{z_t(x)}_{Initial\,Distribution} dx \tag{1}$$

The stochastic kernel estimation can usually be evaluated by dividing the joint probability density function $z_{t,t+s}(y,x)$ by the marginal probability density function $z_t(x)$:

$$z_{t+s|Z_t=x}(y) = \frac{z_{t,t+s}(y,x)}{z_t(x)} \tag{2}$$

One approach to calculate these parameters relies on the discretization of the Z space. However in this study we prefer to retain a continuous Z space and will analyze convergence and the presence of convergence clubs by plotting modal boxplots, as suggested by Hyndman et al (1996). [1].

2.3 Spatial Autocorrelation

There are several statistics for testing spatial autocorrelation in the literature. In this study the Moran's I statistic will be used. This statistic was suggested by Moran (1948) and can be defined as the coefficient of the correlation of the spatially lagged variable on the regular variable. Given a weight matrix $W = w_{ij}$ and a variable z_i which can be associated to each region i, the Moran's statistic I can be defined as:

[1] For a more detailed presenatation of the distributional approach see Magrini (2009); Mendez (2018, 2017)

$$I = \frac{\sum_i \sum_j w_{ij} z_i . z_j}{\sum_i z_i^2} = \frac{\sum_i (z_i \times \sum_j w_{ij} z_j)}{\sum_i z_i^2}$$

Given that the statistic is the coefficient of an OLS regression, it has an associated significance p-value. However given its spatial significance it also has a pseudo p-value obtained by a randomization simulation. For more details on this significance see the Geoda documentation Anselin et al (2006).

In addition, one procedure to analyse the robustness of the standar Moran's I is to control for locational fixed effects. To remove these fixed effects the Moran's I for the variable $z_{i,t} z_{i,t1}$ is reported. This means that If at location i a fixed effect μ_i is present, it is possible to have $z_{i,t}$ as composed by some intrinsic value and the fixed effect: $z_{i,t} = z*_{i,t} + \mu_i$. Subtracting the variables for consecutive years will then remove the fixed effect μ_i. By utilizing differential Moran scatter plots and by calculating the Moran's I it he robustness of the conventional Moran's I can be evaluated.

2.4 The Getis Filter

From early studies in the regression framework of convergence analysis, it has been assumed that each region develops independently and reaches its stable state. However, more recent studies have tried to deal with the spatial Independence "hypothesis" by including spatial models when doing regressions; for example, two of the first studies to include spatial effects in growth regressions are Rey and Montouri (1999) and Bernat Jr (1996). A different approach to deal with strong spatial autocorrelation signs is to filter the variables and express them as the sum of a spatially dependent and a spatially independent components.

One of the filters reported in the literature is known as the Getis filter Getis and Griffith (2002). This approach requires of four steps: 1) evaluating the local G spatial statistic for each region for a number of increasing distances; 2) the distance d_i for which the statistic decreases for each region i is found; 3) the mode d_m of the distribution of d_i is found; and 4) the filtering of variable x_i for each region using the following equation:

$$x_i^* = \frac{x_i(W_i)}{(n-1)G_i(d_m)} \tag{3}$$

Where x_i^* is the filtered variable, n is the number of observations, W_i is the sum of all geographic links usually weighted so that is just includes the neighbors which are at closer distances than d_m , and $G_i(d_m)$ is the statistic of Getis and Ord (2010).

It is necessary to clarify that such filtration includes several restrictions on the variables so that as Getis and Griffith state "The use of this approach is limited by the nature of the 1992 version of the $G_i(d_m)$ statistic. All variables must have a natural origin and be positive" Getis and Griffith (2002). In our case the variable to be studied is regional GDP per capita which is positive and have a clear nartural origin and thus can be decomposed using the Getis filter.

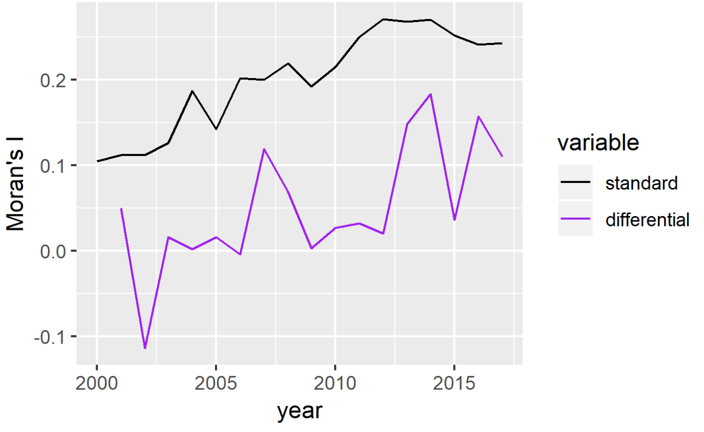


Fig. 2: Differential and standard Moran's I at the district level

3 Results

As explained in the previous section the application of the Getis filter requires that the data shows strong signs of spatial autocorrelation. In the case of provincial data (34 provinces) it was found that there are no signs of spatial autocorrelation for Regional GDP Per Capita (GDPpc) for any year in the period 2000-17, with the Moran's I statistic being not being statistically different from 0. This results do not change weather we use a distance band or a queen contiguity criteria when creating the spatial weights matrix.

In contrast, In the case of the district level data, using a queen contiguity criteria for the Thiessen polygons, it turns out that the Moran's I at the district level is significant with a $p-value < 0.01$ for all years from 2000 up to 2017. However, by using the differential Moran's I it is found that this latter statistic is robust for certain periods 2000-2003, 2006-2008 and continuously from 2013. As it is common in the literature (see the Geoda documentation) the value of the differential Moran's I is significantly smaller that the one reported for the standard Moran's I.

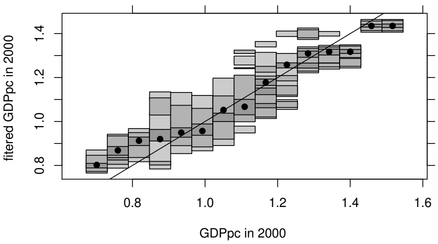
In Figure 2 the magnitude of both Moran's I statistic can be seen. In addition, it can be stated that the standard statistic uniformly increased from 2000 up to 2012 and then it stabilized at around 0.25. Moreover, in the case of the differential statistics (purple line) the pattern is more erratic being significant and negative at the beginning while turning positive and significant from 2013.

Assuming that strong signs of spatial autocorrelation are present as shown in Figure 2 we proceeded to find the critical distance d_m. Following the process explained in the methods sections the critical distance found was $d_m = 338km$. Using this distance and replacing in the equation 3 the spatial and non spatial component of Regional GDP per capita for each location and year are found.

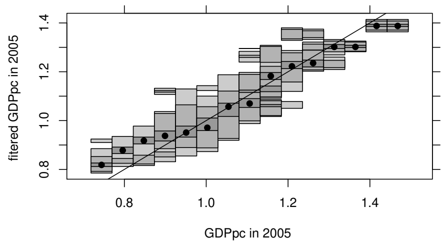
One way to evaluate the presence of spatial effects is to analyse the data by using the distributional dynamics framework. Although, this analysis is usually done for different years as explained in the methods section of this paper; instead of using the transformation not for different years we study the transition form the original variable to the filtered non-spatial variable as set by equation 3. The modal boxplots for several years are shown in Figure 3. From all panels in Figure 3 it can be stated that the distribution is different from the trivial 45 degrees line (the diagonal in all boxplots), in fact in all panels it is clear that joining the modes (black dots in the graphs) creates an S-shape curve. This curves present a variety of convergence clubs ranging from 2 to 3 clubs depending on the year.

Fig. 3: Distributional convergence and clusters for several years rates

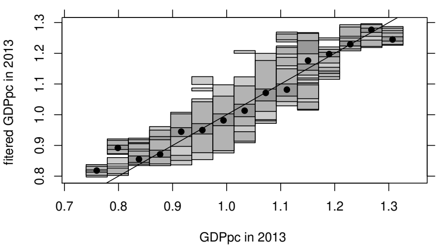
(a) Modal boxplot for year 2000



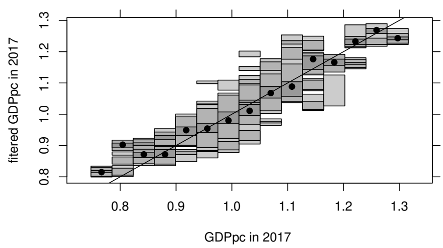
(b) Modal boxplot for year 2005



(c) Modal boxplot for year 2013



(d) Modal boxplot for year 2017



A dynamical analysis (for different years) can also be done as explained in the methods section of this paper. Taking as the initial time the year 2000 and as the final time the year 2017 the modal bosxplots are presented in Figure 4; in panel (a) the original data was used and in panel (b) the filtered data was used. In both panels the s-shape curves present a pattern far from the trivial diagonal line. The most remarkable difference in the two panels is that in panel (b) the members of the lower and upper clubs increase (see the dots in the upper and lower tails of the curve).

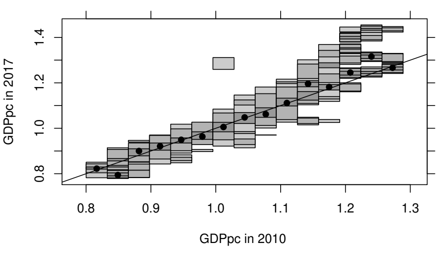
It is even possible to state that for the original data in panel (a) may not have robust convergence clubs.

If the filtered data has some of least developed regions evolving to lower GDPpc levels and some of the most developed regions evolving to even higher GDPpc levels it can be seen that the unfiltered data shows overall strong divergence patterns. In this sense is space which compresses the distribution and evens out the development of all regions so that the lower and upper convergence clubs (overall divergence of the distribution) disappear as seen in panel (a) with original data.

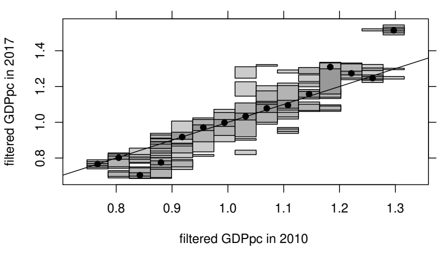
Comparing the dynamics of the filtered and unfiltered data we conclude that even though there are no robust sings of convergence of the unfiltered data or the formation of convergence clubs, but the spatial effects have induced the uniform progress of most regions. While for the filtered data (spatially-independent) shows patterns of polarization were reported. Thus, it has been found that spatial effects reduce polarization. In other words, spatial dependence helps to scale down regional disparities in Regional GDP per capita.

Fig. 4: Distributional convergence and clusters- Dynamic transitions rates

(a) Modal boxplot 2000-2017 original data



(b) Modal boxplot 2000-2017 filtered data



4 Concluding Remarks

The issue of whether poor districts are converging to the level of richer districts after the implementation of decentralization is an important concern for policymakers in Indonesia. This study has pointed out two results for policy discussion. First, for the lowest and highest income range, the distributional convergence analysis shows that spatial effects account for the income dynamics of Indonesia at the district level. However, comparing the several years, it can be seen that the distribution of both clubs become more persistent (approaching the diagonal line). In the context of policy discussion, these results bring a policy message that during the decentralization period, the economic performance of the districts in general was likely tend to be influenced positively by the neighboring districts performance.

Secondly, compared to the transition dynamics of the unfiltered distribution, the filtered distribution shows some degree of mobility (polarization) at the top and bottom income distribution. According to Fischer and Stumpner (2010), in order to avoid misleading interpretations on evaluating cross-regional growth and convergence dynamics, the analysis should be conducted using spatially filtered data. Thus, the findings are in line with the previous analysis such Vidyattama (2013) that show a significant role of neighbor effects in reducing inequality in Indonesia during the decentralization period.

The contribution of this study is two fold. The construction of a balanced panel dataset allows us to analyse the patterns of all districts in Indonesia in post-decentralization. The spatially filtered data calculated by Getis spatial filter help us evaluate the convergence dynamics across districts more precisely. For further research, the study can be extended by including the neighbour effects on the speed convergence.

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