Growth in East Java : Convergence or Divergence ?

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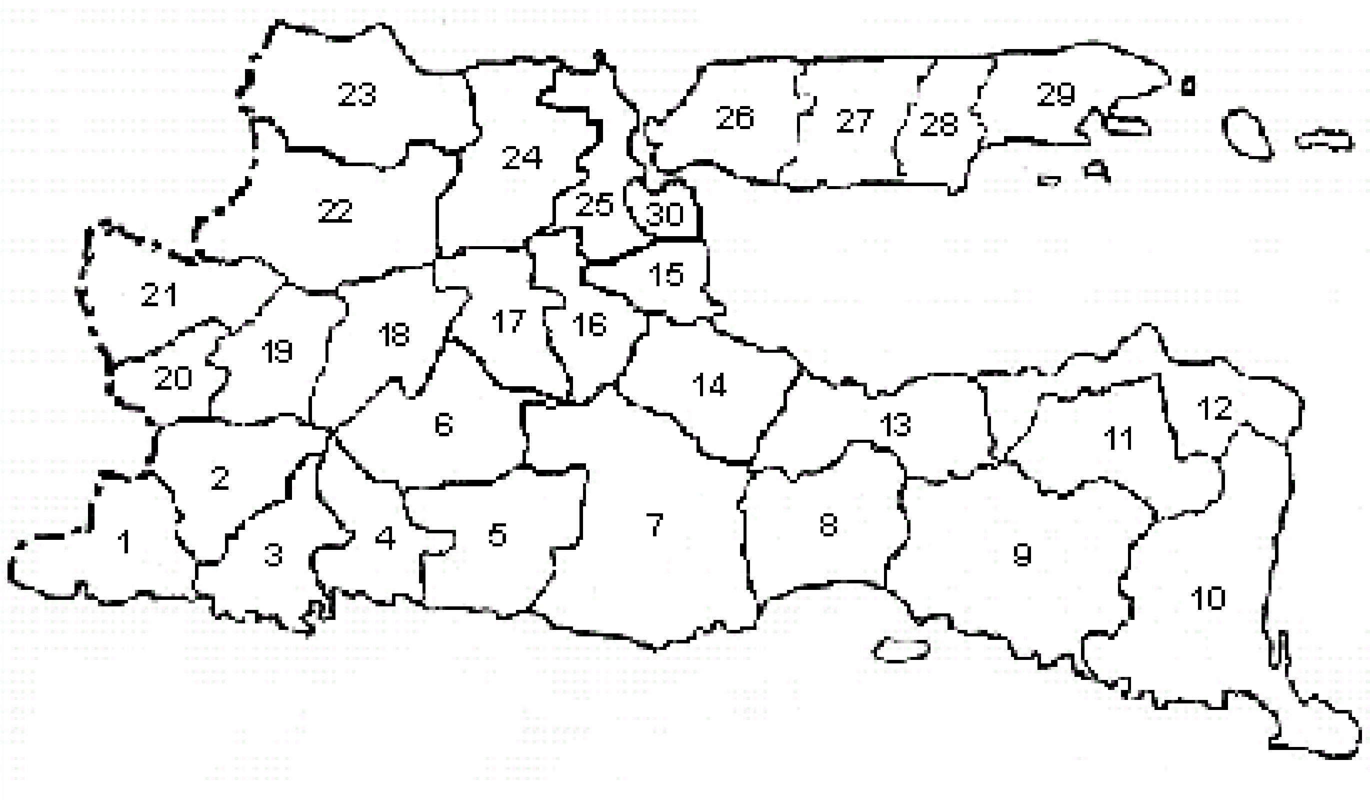
Abstract

This study try to identify the β-convergence process among regions in East Java using cross-section data of 30 regions for period 1983-2001, taking into account the presence of spatial heterogeneity and spatial dependence. Detection of spatial regimes using G-I* statistics on regional per capita GDP values in 1983 found cluster of high income regions (group of "rich") in central & eastern part of East Java, and cluster of low income regions (group of "poor") in western part. The result of OLS & GLS regression on absolute convergence model does not found any convergence process in East Java regional income. The convergence process is only found in spatial cross regressive absolute β-convergence model estimated for spatial club A (group of "rich"), but there is no evident for the same convergence process is happening in spatial club B (group of "poor"). Using the spatial cross-regressive model for absolute β-convergence this study founds that the coefficient of spatial lag of initial income (τ) is positive and significant in every equations. This shows how the spatial dependence has a significant contribution in explaining regional income growth in East Java. The positive and significant sign of (τ), means that the growth of a region is affected by initial income of its neighbors. The region which surrounded by wealthy neighbors will grow faster than the region surrounded by poor neighbors. The effect of neighbor's initial income level to the growth of a region can be a result of technological or pecuniary spillovers. This will be the situation when technology or cost of production in a region depends not just on factors within the region but also on the level of technology in the neighbors (technology is embodied in in factors of production). These effects can be consider as supply-side externalities

Keywords : β-convergence, spatial heterogeneity, spatial dependence

Figure 1. East Java Regions by Geographic Zone



01_Pacitan	07_Malang	13_Probolinggo	19_Madiun	25_Gresik
02_Ponorogo	08_Lumajang	14_Pasuruan	20_Magetan	26_Bangkalan
03_Trenggalek	09_Jember	15_Sidoarjo	21_Ngawi	27_Sampang
04_Tulungagung	10_Banyuwangi	16_Mojokerto	22_Bojonegoro	28_Pamekasan
05_Blitar	11_Bondowoso	17_Jombang	23_Tuban	29_Sumenep
06_Kediri	12_Situbondo	18_Nganjuk	24_Lamongan	30_Surabaya

I. INTRODUCTION

The issue of regional disparities has received considerable attention in economic research since 1990. The development of new growth theory and new economic geography is one of the reason behind the renewed interest in this topic, starting with the work of *Romer* (1986, 1990), *Lucas* (1988) and *Krugman* (1991). Concerning the implications for regional disparities, the new theoretical approaches have an important similarity. The result, convergence or divergence, depends crucially on details of the models (*Niebuhr*, 2001). Thus, theory alone can not provide explicit conclusions with regard to the development of regional disparities. The issue, whether regional per capita income tends to converge, remains a task of empirical research.

The majority of empirical studies on convergence apply a methodology that bases on the Solow-Swan model which is the prediction of absolute or conditional convergence. The model implies that economies grow faster the further they are from their steady state value. Thus, assuming the same steady state, poor economies tend to realise a higher growth of per capita income than rich ones. If the steady states differ, the concept of conditional convergence has to be considered (see *Barro* and *Sala-i-Martin,* 1995).

Until the mid of the 1990s, most tests for convergence consisted of cross-sectional regressions, with income growth as the dependent variable and the initial level of income as explanatory variable. This approach was applied to various samples of nations and regions. Frequently, additional variables were included on the right hand side in order to control for differences in the steady states (e.g. *Barro* and *Sala-i-Martin,* 1995 or *Mankiw*, *Romer* and *Weil,* 1992). Following this research tradition, several studies have been conducted to identify regional income convergence in Indonesia (*Saldanha*, 2003 and *Wibisono*, 2001, 2003) using various methodology from classic cross-section regression on absolute convergence (*Saldanha*, 2003) until panel regression using SUR and GLS (*Wibisono*, 2001, 2003).

This paper is an attempt to provide information on the spatial effect of convergence in East Java, since majority of convergence studies in Indonesia fail to consider and model spatial effect (most of those studies view the region as an isolated entity and neglected the role of spatial interaction) and none of them have ever analyze the convergence process in provincial level.

The rest of the paper is organized as follows. In section 2 the theoretical approach is discussed. In section 3 the data and spatial weights matrix are described. The exploratory spatial data analysis [ESDA] of the initial per capita income will be presented in Section 4. Section 5 and 6 will be discussed the empirical methodology applied and the empirical result. Section 7 concludes.

II. THEORETICAL APPROACH

Since the publication of the seminal articles of *Barro* and *Sala-i-Mart*in (1991, 1995), numerous studies have examined β-convergence between different countries and regions. This concept is rooted from the neoclassical growth model, which predicts that the growth rate of a region is positively related to the distance that separates it from its steady state. Empirical evidence for β-convergence has usually been investigated by regressing growth rates of GDP on initial levels.

There are two concepts that usually considered in the literature. If all economies are structurally identical and have access to the same technology, they are characterized by the same steady state, and differ only by their initial conditions. This is the hypothesis of *absolute* β-convergence, which is usually tested on the following cross-sectional model :

$$\frac{1}{t}\ln\left(\frac{y_{i,t}}{y_{i,0}}\right)=\alpha+\beta\ln\left(y_{i,0}\right)+\varepsilon_i \quad ; \quad \varepsilon_i \sim i.i.d.\left(0,\sigma_\varepsilon^2\right) \tag{1}$$

where $y_{i,t}$ represents GRP per capita in region i year t; α, β are parameter to be estimated and ε_i is a stiochastic error term. There is β-absolute convergence when the estimate of β is significantly negative.

The concept of *conditional* β-convergence is used when the assumption of similar steady-states is relaxed. Note that if economies have very different steady states, this concept is compatible with a persistent high degree of inequality among economies. It is usually tested on the following cross-sectional model:

$$\frac{1}{t}\ln\left(\frac{y_{i,t}}{y_{i,0}}\right)=\alpha+\beta\ln\left(y_{i,0}\right)+\gamma X_i+\varepsilon_i \quad ; \quad \varepsilon_i \sim i.i.d.\left(0,\sigma_\varepsilon^2\right) \tag{2}$$

where X_i is a vector of variables, maintaining constant the steady state of region i. There is β-absolute convergence when the estimate of β is significantly negative once X is held constant.

A key limitation of the majority of empirical analyses of cross-sectional regional growth has been the assumption that regions are considered as isolated entities, as if their geographical location and potential in the regional linkages would not matter (*Fischer* and *Stirböck*, 2004). Despite the fact that theoritical mechanism of technological diffussion, factor mobility, and transfer of payments that argued to drive the regional convergence phenomenon have explicit geographical components, the role of spatial effects in the regional convergence studies has virtually be ignored. Only recently, the role of spatial effects has been considered in empirical studies using formal tools of spatial statistics and econometrics (*Dall'erba* and *Le Gallo*, 2003; *Abreu* and *Florax*, 2004).

Following *Anselin* (1988), spatial effects refer to both spatial dependence and spatial heterogeneity. Spatial autocorrelation can be defined as the coincidence of value similarity with locational similarity. Therefore, there is positive spatial autocorrelation when similar values of a random variable measured on various locations tend to cluster in space. Applied to the study of income disparities, this means that rich regions tend to be geographically clustered as well as poor regions.

Integrating spatial autocorrelation into β-convergence models is useful for three reasons. First, from an econometric point of view, the underlying hypothesis in OLS estimations is based on the independence of the error terms, which may be very restrictive and should be tested since, if it is rejected, the statistical inference based on it is not reliable. Second, it allows capturing geographic spillover effects between European region using different spatial econometric models: the spatial lag model, the spatial error model or the spatial cross-regressive model (*Rey* and *Montouri*, 1999). Third, spatial autocorrelation allows accounting for variations in the dependent variable arising from latent or unobservable variables. Indeed, in the case of β-convergence models, the appropriate choice of these explanatory variables may be problematic because it is not possible to be sure conceptually that all the variables differentiating steady states are included.

Spatial heterogeneity means in turn that economic behaviors are not stable over space. In a regression model, spatial heterogeneity can be reflected by varying coefficients, i.e. structural instability, or by varying error variances across observations, i.e. heteroskedasticity. These variations follow for example specific geographical patterns such as East and West, or North and South. Such a spatial heterogeneity probably characterizes patterns of economic development under the form of spatial regimes and/or groupwise heteroskedasticity: a cluster of rich regions (the core) being distinguished from a cluster of poor regions (the periphery).

Spatial heterogeneity can be linked to the concept of convergence clubs, characterized by the possibility of multiple, locally stable, steady state equilibria. A convergence club is a group of economies whose initial conditions are near enough to converge toward the same long-term equilibrium. Under such circumstances there might be convergence among similar types of economies (club convergence), but little or no convergence between such clubs. When convergence clubs exist, one convergence equation should be estimated per club. To determine those clubs, some authors select a priori criteria, like the belonging to a geographic zone or some GDP per capita cut-offs. Others prefer to use endogenous methods, as for example, polynomial functions or regression trees. In the context of regional economies characterized by strong geographic patterns, like the core-periphery pattern, convergence clubs can be detected using exploratory spatial data analysis which relies on geographic criteria (*Dall'erba* and *Le Gallo*, 2003; *Fischer*, *Manfred* and *Stirböck*, 2004).

Club identification in this study is performed with the help of exploratory spatial data analysis [ESDA] focusing on the explanatory variable that defines the initial conditions of the convergence process. This technique is a convenient way of detecting spatial regimes in the data (for more details see Section 4). The virtue of the procedure lies in its ability to uncover spatial effects and spillovers among regional economies on the basis of initial incomes.

III. DATA AND SPATIAL WEIGTHS MATRIX

This study use data on percapita GRDP (Gross Regional Domestic Product) of each East Java's regions in logarithms over the 1983-2001 period. The sample is composed of 37 regencies (*kabupaten*) and municipialities (*kota*) which extracted from *"Jawa Timur dalam Angka"* published by Central Bureau of Statistics (BPS). For ease of calculation, the 37 municipialities is augmented to 30 regions by integrating regencies which has municipialities (7 municipialities) into a single geographic entities. This step is taken considering the fact that most municipialities are geographicaly located inside its regencies (region within region).

Spatial Weights Matrix

The spatial weight matrix is the fundamental tool used to model the spatial interdependence between regions. More precisely, each region is connected to a set of neighboring regions by means of a *purely spatial pattern* introduced *exogenously* in this spatial weight matrix $\boldsymbol{W}$. The elements of w_{ii} on the diagonal are set to zero whereas the elements w_{ij} indicate the way the region i is spatially connected to the region j. These elements are *non-stochastic, non-negative* and *finite*. In order to normalize the outside influence upon each region, the weight matrix is standardized such that the elements of a row sum up to one. For the variable y_0, this transformation means that the expression $\boldsymbol{Wy_0}$, called the spatial lag variable, is simply the weighted average of the neighboring observations. Various matrices can be considered: a simple binary contiguity matrix, a binary spatial weight matrix with a distance-based critical cut-off, above which spatial interactions are assumed negligible, more sophisticated generalized distance-based spatial weight matrices with or without a critical cut-off. The notion of distance is quite general and different functional form based on distance decay can be used (for example inverse distance, inverse squared distance, negative exponential etc.). The critical cut-off can be the same for all regions or can be defined to be specific to each region leading in the latter case, for example, to *k*-nearest neighbors weight matrices when the critical cut-off for each region is determined so that each region has the same number of neighbors.

This study use the traditional approach (a general spatial weight matrix) that is based on the geography of the observations, designating regions as 'neighbours' when they are share border of each other (a simple binary contiguity matrix). According to the adjacency criteria, the element of the spatial weight matrix (w_{ij}) is one if location i is adjacent to location j, and zero otherwise. For ease of interpretation, the matrix is standardized so that the elements of a row sum to one (*row-standardized*).

IV. EXPLORATORY SPATIAL DATA ANALYSIS

A convergence club is a group of regional economies that interact more with each other than with those outside and that exhibit initial conditions which are near enough to converge towards the same long-run equilibrium.

Unfortunately, economic theory does not provide guidance as to either the number of clubs or the way in which the explanatory variable defining the initial conditions determines clubs (*Fischer* and *Stirböck*, 2004). To determine those clubs, some authors select a priori criteria, like the belonging to a geographic zone or some GDP per capita cut-offs, others prefer to use endogenous methods, as for example, polynomial functions or regression trees. In the context of regional economies characterized by strong geographic patterns, like the core-periphery pattern, convergence clubs can be detected using exploratory spatial data analysis which relies on geographic criteria (*Dall'erba* and *Le Gallo*, 2003; *Fischer*, *Manfred* and *Stirböck,* 2004).

Two statistical measures of exploratory spatial data analysis [ESDA] which this study use to determine spatial clubs are *Moran* scatter plot (*Ertur*, *Le Gallo* and *Baumont*, 2004) and *Getis-Ord* statistics (*Fischer*, *Manfred* and *Stirböck,* 2004). Focusing on the explanatory variable that defines the initial conditions of the convergence process, these techniques are convenient way of detecting spatial regimes in the data. The virtue of the procedures lies in its ability to uncover spatial effects and spillovers among regional economies on the basis of initial incomes.

Using the spatial weight matrices previously described, the first step of our analysis is to detect the existence of spatial heterogeneity in the distribution of regional per capita GDP 1983. In that purpose, we use the G-I* statistics developed by *Ord* and *Getis* (1995). These statistics are computed for each region and they allow detecting the presence of local spatial autocorrelation: a positive value of this statistic for region *i* indicates a spatial cluster of high values, whereas a negative value indicates a spatial clustering of low values around region *i*. Based on these statistics, we determine our spatial regimes, which can be interpreted as spatial convergence clubs, using the following rule: if the statistic for region *i* is positive, then this region belongs to the group of "rich" regions and if the statistic for region *i* is negative, then this region belongs to the group of "poor" regions. The statistic allows to identify spatial regimes in the data by use of the concept called proximal space (*Getis* and *Ord,* 1992 and *Ord* and *Getis* 1995) and is formally defined as

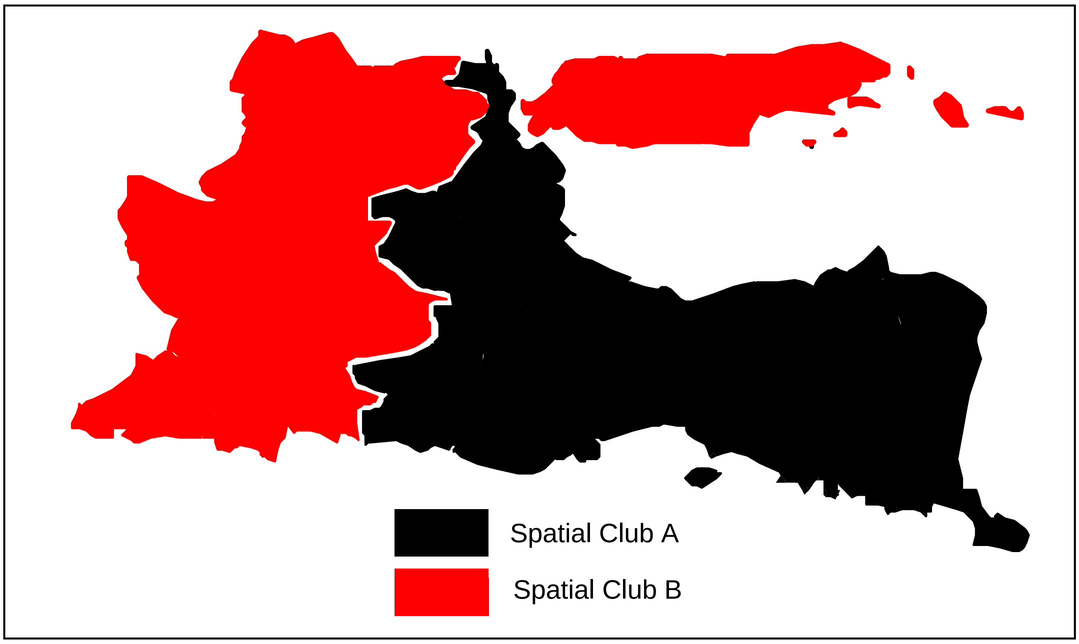
$$Gi = \sum_{j}^{n} w_{ij} \, (x_j - \bar{x}_i) \Big/ \left(S_i \sqrt{\frac{w_i(n-1-w_i)}{n-2}}\right) \qquad \textbf{(3)}$$

where x_i is the observed value at location *i*, $\bar{x}_i = \frac{1}{n-1}\sum_{j,j\neq i}^{n} x_j$,(w_{ij}) is a symmetric binary spatial weight matrix $w_i = \sum_{j,j\neq i}^{n} w_{ij}$ and $S_i^2 = \frac{1}{n-1}\sum_{j,j\neq i}^{n}(x_j - \bar{x}_i)^2$

The G-I* statistics can be used to identify spatial agglomerative patterns with high-value clusters or low-value clusters. However, this statistic cannot identify the negative spatial association (i. e., high value with surrounding low values and vice versa).

The result of this procedure outlined in Figure 2. Two spatial regimes, where richer regions tend to be clustered in club A and poorer regions in club B. This geographical pattern can be seen as representative of the well-known core-periphery framework (*Krugman* 1991; *Fujita* et al., 1999).

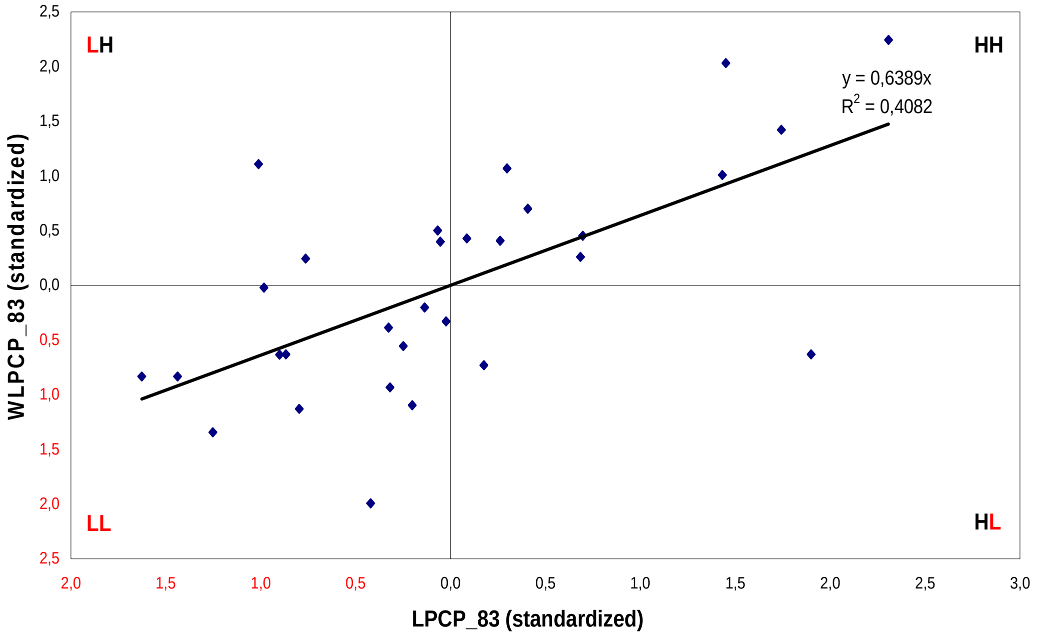
Figure 2. Two spatial regimes identified by using G-I* Statistics [per capita GRDP in 1983]



Spatial club A consists of 14 regions in central & eastern part of East Java includes : Blitar, Malang, Lumajang, Jember, Banyuwangi, Bondowoso, Situbondo, Probolinggo, Pasuruan, Sidoarjo, Mojokerto, Jombang, Gresik, Surabaya. Meanwhile *Spatial club B* is made up of 16 regions in western part of East Java includes : Pacitan, Ponorogo, Trenggalek, Tulungagung, Kediri, Nganjuk, Madiun, Magetan, Ngawi, Bojonegoro, Tuban, Lamongan, Bangkalan, Sampang, Pamekasan, Sumenep.

The next step of our analysis is using the Moran scatter plot to detect the existence of spatial heterogeneity in the distribution of East Java regional per capita GDP 1983. This measures has advantage from the G-I* statistics because it can identify the negative spatial association (i. e., high value with surrounding low values and vice versa) which G-I* statistics cannot detect (Figure 3 outline the result). The Moran scatterplot is illustrative of the complex interrelations between global spatial autocorrelation and spatial heterogeneity in the form of spatial regimes. Global spatial autocorrelation is reflected by the slope of the regression line of $\boldsymbol{Wy_0}$ against $\boldsymbol{y_0}$, which is formally equivalent to the Moran's I statistic for a row standardized weight matrix (*Ertur, Le Gallo and Baumont,* 2004).

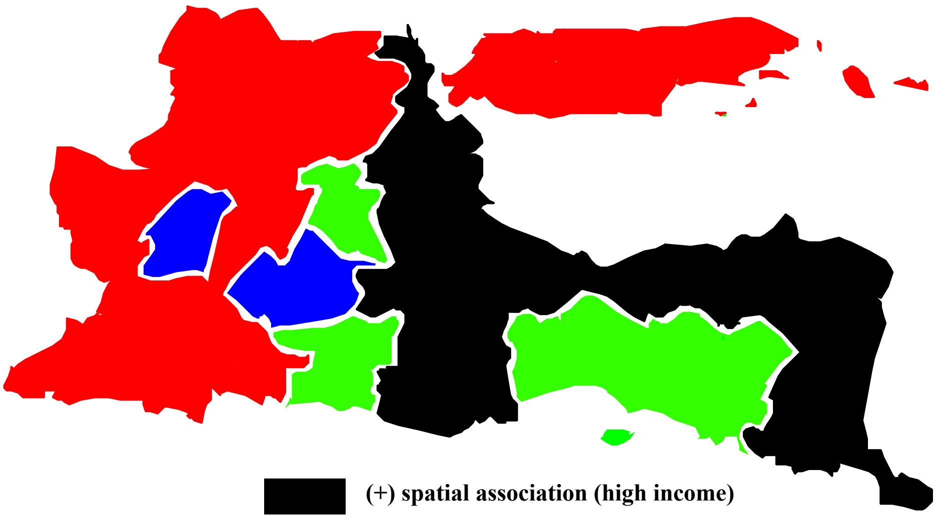
Figure 3. Moran Scatterplot for LPCP_83 (30 Regions)



The Moran scatterplot displays the spatial lag $\boldsymbol{Wy_0}$ against $\boldsymbol{y_0}$, both standardized. The four different quadrants of the scatterplot correspond to the four types of local spatial association between a region and its neighbors (Figure 4 outline the result): (HH) a region with a high value surrounded by regions with high values, (LH) a region with a low value surrounded by regions with high values, (LL) a region with a low value surrounded by regions with low values, (HL) a region with a high value surrounded by regions with low values. Quadrants HH and LL refer to positive spatial autocorrelation indicating spatial clustering of similar values (positive spatial association) whereas quadrants LH and HL represent negative spatial autocorrelation indicating spatial clustering of dissimilar values (negative spatial association). The Moran scatterplot may thus be used to visualize atypical localizations in respect to the global pattern, i.e. regions in quadrant LH or in the quadrant HL. A four-way split of the sample based on the two control variables, initial per capita GDP and initial spatially lagged per capita GDP, allowing for interactions between them, can therefore be based on this Moran scatterplot.

The result of both measures suggests some kind of spatial heterogeneity in the East Java regional economies, the convergence process, if it exists, could be different across regimes. However this study will only consider the spatial clubs constituted by the G-I* statistics, since using Moran scatterplots to determine the spatial clubs imply that the "*atypical*" regions (regions in quadrant LH and the quadrant HL) must be dropped out of the sample (*Dall'erba and Le Gallo,* 2003), which means 6 regions in this study (that is 20% from observation!!). Therefore this study decide that the use of Getis-Ord statistics is more appropriate in order to be able to work with the entire sample.

Figure 4. Spatial regimes identified by using Moran Scatter Plot
[per capita GRDP in 1983]



V. β-CONVERGENCE MODELS AND SPATIAL EFFECTS

There are three alternative specifications to capture the spatial dependence into β-convergence models (*Rey* and *Montouri,* 1999) : *the spatial lag model*, *the spatial error model* and *the spatial cross-regressive model*. Most studies in this area use the spatial lag model & the spatial error model to deal with spatial dependence after previously conduct several diagnostic test (Lagrange Multiplier test) to decide whether a spatial lag or a spatial error model of spatial dependence is the most appropriate (*Abreu, de Groot* and *Florax*, 2004). However this study choose the spatial cross-regressive model by *a priori* and does not go along those standard procedure to decide the right specifications of spatial dependence for two reason. First, spatial cross-regressive model is relatively simple from other specifications of spatial dependence, since its estimation can be based on OLS (*Rey* and *Montouri,* 1999). Second, this approach has the advantage of confining the spatial effects to the neighbours of each observation (as defined by the spatial weights matrix) because the cross-regressive model is a model which is local in scope (*Abreu, de Groot* and *Florax,* 2004).

In general, the spatial lag model and the cross-regressive model with a spatially lagged income level tend to explain the same spatial growth effect, i.e. that regional income growth is affected by both the local income level and the initial income in adjacent regions. However, whereas the spatial interaction in the spatial lag approach extends over the entire regional system, of course with declining intensity due to a distance decay, the spatial effects in the cross-regressive model are restricted to regions that are adjacent according to the matrix $\boldsymbol{W}$ (*Niebuhr,* 2001).

Spatial Cross-Regressive Model of absolute β-convergence can be construct by adding the spatial lag of starting per capita incomes to the original specification:

$$\frac{1}{t}\ln\left(\frac{y_{i,t}}{y_{i,0}}\right) = \alpha + \beta \ln\left(y_{i,0}\right) + \tau W \ln\left(y_{i,0}\right) + \varepsilon_i \quad ; \quad \varepsilon_i \sim i.i.d.\left(0, \sigma_\varepsilon^2\right) \qquad \textbf{(4)}$$

This Equation (4) can be reformulated in matrix form as

$$\boldsymbol{g} = \boldsymbol{Y}\boldsymbol{\gamma} + \boldsymbol{\varepsilon} \qquad \textbf{(5)}$$

where $\boldsymbol{g}$ is a (N, 1)-vector of observations on the dependent variable for the N regions. The (3, 1)-vector $\boldsymbol{\gamma}$ consists of three components: $\boldsymbol{\alpha}, \boldsymbol{\beta}$ and τ in the notation of Equation (4). The second and third component is the coefficient of the explanatory variable: log-normal of initial per capita GRP and its spatial lag. The coefficient $\boldsymbol{\alpha}$ is a constant term and can be interpreted as the coefficient of an exogenous (explanatory) variable which takes the unit value for each of the N observations. Thus, $\boldsymbol{Y}$ is a (N, 3)-matrix of observations on the three exogenous variables. $\boldsymbol{\varepsilon}$ is a (N, 1)-vector of random disturbance terms. For the data-generating process it is assumed that the elements of the random vector $\boldsymbol{\varepsilon}$ are identically and independently distributed (*i.i.d.).* Thus, the error variance-covariance matrix is $E\,[\varepsilon\varepsilon'] = \boldsymbol{\sigma^2}\, \boldsymbol{I_N}$, where the scalar is $\boldsymbol{\sigma^2}$ unknown, $\boldsymbol{I_N}$ a Nth-order identity matrix and $\boldsymbol{\varepsilon'}$ denotes the transpose of $\boldsymbol{\varepsilon}$. The parameter $\boldsymbol{\gamma}$ can be estimated by means of ordinary least squares [OLS].

It is straightforward to adopt this spatial cross-regressive β-convergence growth regression framework to account for club convergence. As explained in the previous section, G-I* statistics has found two spatial clubs (group of “rich”-Club A and group of “poor”-Club B) which can be indicated by the indices A and B. These clubs correspond to subsets of the observations for which the regression model follows a different set of coefficients. Each club may be represented by a different cross-sectional equation. Then the *two-club growth regression model* can formally be expressed as

$$\begin{bmatrix} g_A \\ g_B \end{bmatrix} = \begin{bmatrix} \boldsymbol{Y}_A & 0 \\ 0 & \boldsymbol{Y}_B \end{bmatrix} \begin{bmatrix} \gamma_A \\ \gamma_B \end{bmatrix} + \begin{bmatrix} \varepsilon_A \\ \varepsilon_B \end{bmatrix} \qquad \textbf{(6)}$$

where $\boldsymbol{g_A}$ and $\boldsymbol{g_B}$ are the dependent variables; $\boldsymbol{Y_A}$ and $\boldsymbol{Y_B}$ the explanatory variables; $\boldsymbol{\gamma_A}$ and $\boldsymbol{\gamma_B}$ the coefficients; and $\boldsymbol{\varepsilon_A}$ and $\boldsymbol{\varepsilon_B}$ the errors in the respective clubs A and B of regions. Let $\boldsymbol{N_A}$ and $\boldsymbol{N_B}$ denote the number of observations in club A and club B, respectively. Then $\boldsymbol{N = N_A + N_B}$.

The simple block structure of the two-club model (6) can be expressed more succinctly in one equation

$$\boldsymbol{g}^* = \boldsymbol{Y}^* \boldsymbol{\gamma}^* + \boldsymbol{\varepsilon}^* \quad \textbf{(7)}$$

where the boldface variables without subscript refer to combined variable, coefficient and error matrices.

Since the full set of elements of the error variance matrix $\Psi = E\,[\varepsilon^* \varepsilon^{*\prime}]$ is generally unknown and cannot be estimated from the data due to a lack of degrees of freedom, it is necessary to impose a simplifying structure. The most straightforward assumption is a model with a constant error variance over the whole set of observations:

$$\Psi = \sigma^2 \boldsymbol{I}_N \quad \textbf{(8)}$$

where σ^2 is the constant error variance. This specification leads to the so-called *classical two-club convergence model* that conforms to the standard assumptions of the classical test methodology.

But this assumption may be overly restrictive. Assuming an error variance that is different in each of the clubs of regions results in a special form of heteroskedasticity

$$\Psi = \begin{bmatrix} \sigma_A^2 \boldsymbol{I}_A & 0 \\ 0 & \sigma_B^2 \boldsymbol{I}_B \end{bmatrix} \quad \textbf{(9)}$$

where σ^2_A and σ^2_B denote the club-specific constant error variances, $\boldsymbol{I}_A$ and $\boldsymbol{I}_B$ are identity matrices of dimensions $\boldsymbol{N}_A$ and $\boldsymbol{N}_B$. This specification results into the *two-club growth regression model with groupwise heteroskedasticity*. Estimation and testing can be carried out by means of fairly straightforward iterative techniques [so-called estimated GLS] or in a maximum likelihood framework (Fischer and Stirböck, 2004).

VI. ESTIMATION RESULT

The estimation results for the traditional convergence in equation (1) as well as for the models that incorporate spatial regimes (clubs) are summarized in Table 1 and 2. In the first table the OLS estimates of the non-spatial model are presented. The coefficient of the initial income level is not significant in all equation. This finding does not provide support for the hypothesis of absolute *β*-convergence. However, it may arise from misspecification of the model from *groupwise heteroskedasticity.* To overcome this problem the model is re-run with GLS procedure to incorporate the presence of *groupwise heteroskedasticity*. The GLS regression result on the classical convergence model in Table 2 still does not provide a support for convergence in East Java. However, the overall fit of the specifications (R^2) seems to favor the two-club convergence model rather than a single steady-state absolute convergence model, both in OLS and GLS regression.

TABLE 1 & 2 TO BE POSITIONED ABOUT HERE

To improve the performance of the regression result, the spatial effect is introduced to the model by incorporating the spatial lag of initial income (*spatial cross-regressive model*). This procedure is taken since Moran scatter plot in Figure 3 shows the existence of a substantial level of spatial dependence among regions in East Java. Table 3 and 4 reports the estimation result for spatial cross-regressive model estimated with OLS and GLS. Further discussion will be focused on the estimation of spatial cross-regressive model with GLS procedure (Table 4) since it is more suitable to deal with the problem of *groupwise heteroskedasticity.*

Estimation of spatial cross-regressive model of absolute β-convergence by GLS in Table 4 shows that the coefficient of β-convergence for a single state convergence equation is positive and not significant (first column), this findings confirm that there is no supporting statistical evident of income convergences towards a single steady state among East Java regions. However, the coefficient of spatial lag of initial income (τ) in the classical convergence model is positive and highly significant. This means that per capita growth of regions in East Java is more affected (positively) by initial income of their neighbors rather than their own initial income. In another words "*the richer your neighbors the faster you grow*", and *vice versa*.

TABLE 3 & 4 TO BE POSITIONED ABOUT HERE

The GLS estimation of two club convergence model in table 4 (second column) shows how the coefficient of β-convergence in *Spatial Club A* is negative and significant leading to income convergence speed of 3,2 percent per year and suggest that it will take 28,5 years for half of the distance between the initial level of income and club A-specific steady-state level to vanish. Unfortunately, the same convergence process is not found in *Spatial Club B.* The coefficient of β-convergence in *Spatial Club B* is positive and not significant, which means there no support for convergence process among regions in *Spatial Club B.*

Another aspect to be noticed from GLS estimation result of two club convergence model in table 4 is the fact that the coefficient of spatial lag of initial income (τ) is positive and significant in both clubs. This shows how the spatial dependence has a significant contribution in explaining regional income growth in both clubs. The positive and significant sign of (τ), means that the growth of a region is affected by initial income of its neighbors. The region which surrounded by wealthy neighbors will grow faster than the region surrounded by poor neighbors.

The effect of income level of neighbors to the growth of a region can be a result of technological or pecuniary spillovers. This will be the situation when technology or cost of production in a region depends not just on factors within the region but also on the level of technology in the neighbors (technology is embodied in in factors of production). These effects can be consider as supply-side externalities (*Vayá, López-Bazo,* and *Artis,* 1998).

VII. CONCLUSION

The paper has attempted to look for the evidence of regional income convergence in the East Java from neoclassical perspectives. Convergence has been failed to identify as a property of the relation between initial income and growth over the sample period 1983-2001. Even though several cross-sectional and panel data analyses of regional growth in Indonesia have found significant evidence of (un)conditional convergence among provincial per capita income (*Saldanha,* 2003 and *Wibisono,* 2001, 2003) majority of such studies fail to consider and model spatial effect (spatial dependence and heterogeneity) and few (or even none) of them have ever analyze the convergence process in provincial level.

The focus of his study has been on the simplest of the convergence models, the unconditional β-convergence model. In contrast to current practice we rejected the assumption of a single stable steady-state in favor of a multiple-regime [club] alternative in which different regional economies obey different linear convergence models when grouped according to initial conditions. The use of the Getis-Ord statistics produced a grouping that seems overall quite reasonable with the data available rather than Moran scatter plot approach. This paper defined club convergence as the club-specific process by which each region belonging to a club moves from a disequilibrium position to its club-specific steady-state position. At the steady-state the growth rate is the same across the regional economies of a club.

There are four major lessons to be gained from the paper. *First*, there is no evidence for unconditional β-convergence in East Java for the time period of observation. The sample of regional economies belonging to club *A* converges in an unconditional sense at a speed of 3,2 percent per year, it suggests that it will take 28,5 years in club *A* for half of the distance between the initial level of income and the steady-state level of the club to vanish. Unfortunately, there is no evidence of the same convergence process is happening for those belonging to club *B*.

Second, spatial dependence has a significant contribution in explaining regional income growth in both clubs. The region which surrounded by wealthy neighbors will grow faster than the region surrounded by poor neighbors. The effect of income level of neighbors to the growth of a region can be a result of technological or pecuniary spillovers. This will be the situation when technology or cost of production in a region depends not just on factors within the region but also on the level of technology in the neighbors (technology is embodied in in factors of production). These effects can be consider as supply-side externalities (*Vayá, López-Bazo,* and *Artis,* 1998).

Third, the study illustrates that the classical convergence test methodology in most of previous convergence studies in mainstream economics is ill designed to analyze regional convergence due to several reasons. First, it cannot identify groupings of regional economies that are converging at different speeds. Second, it neglects spatial effects that represent spatial interactions and spillovers among the regional economies.

Last but not least, ignoring the presence of spatial dependence and heterogeneity in convergence analysis carried out with cross-sectional data can lead to wrong conclusions, for example, with respect to the assessment of convergence speed. Thus, incorporating for the presence of spatial dependence and heterogeneity by means of appropriate diagnostics and implementing alternative specifications of the convergence test equation when needed are crucial issues in income convergence analysis.

RERERENCES

Abreu, M., H. de Groot and R. Florax (2004). 'Space and Growth', Tinbergen Institute Discussion Paper, no. 129/3, Amsterdam

Anselin, L. (2002). 'Under the Hood. Issues in the Specification and Interpretation of Spatial Regression Models', *Agricultural Economics*, 27, pp. 247-267.

Anselin, L. (2003). 'Spatial Externalities, Spatial Multipliers and Spatial Econometrics', *International Regional Science Review*, 26, pp. 153-166.

Barro, R.J. (1991). 'Economic Growth in a Cross Section of Countries', *Quarterly Journal of Economics*, 106, pp. 407-443

Barro, R.J. and Sala-I-Martin, X., (1995). *Economic Growth*. McGraw-Hill, New York.

Carrington, A. (2003). 'A Divided Europe? Regional Convergence and Neighbourhood Effects', *Kyklos,* 56, pp. 381-394.

Dall'erba, S. and J. Le Gallo (2003). 'Regional Convergence and the Impact of European Structural Funds over 1989-1999: A Spatial Econometric Analysis', University of Illinois at Urbana-Champaign, REAL Working Paper, no. 03-T-14, Urbana.

Ertur, C., J. Le Gallo and C. Baumont (2004). 'The European Regional Convergence Process,1980-1995: Do Spatial Regimes and Spatial Dependence Matter?', *International Regional Science Review*, forthcoming.

Fischer, Manfred M. and C. Stirböck (2004). 'Regional Income Convergence in the Enlarged Europe, 1995-2000: A Spatial Econometric Perspective', ZEW Discussion Paper No. 04-42

Fujita, M., Krugman, P., Venables, A.J., (1999). *The Spatial Economy*. The MIT Press, Cambridge, Massachusetts.

Gustavsson, P. and J. Persson (2003). 'Geography, Cost-of-Living, and Determinants to Economic Growth: A Study of the Swedish Regions, 1911-1993', Stockholm School of Economics, EIJS Working Paper, no. 186, Stockholm.

Kosfeld, R., H.-F. Eckey and C. Dreger (2002). 'Regional Convergence in Unified Germany: A Spatial Econometric Perspective', University of Kassel, Department of Economics Working Paper, no. 39/02, Kassel

Krugman, P., (1991). *Geography and Trade*. The MIT Press, Cambridge, Massachusetts

Le Gallo, J. and S. Dall'erba (2003). 'Spatial Econometric Analysis of the Evolution of the European Convergence Process, 1980-1999', Washington University, Economics Working Paper Archive at WUSTL, no. 0311001, Washington DC.

Lucas, R.E. Jr., (1988). "On the mechanics of economic development". *Journal of Monetary Economics* 22, 3-42

Mankiw, N.G., Romer, D., Weil, D. (1992). "A contribution to the empirics of economic growth". *Quarterly Journal of Economics* 107, 407–437.

Maurseth, B. (2001). 'Convergence, Geography and Technology', *Structural Change and Economic Dynamics*, 12, pp. 247-276.

Moreno, R. and B. Trehan (1997). 'Location and the Growth of Nations', *Journal of Economic Growth*, 2, pp. 399-418.

Niebuhr, A. (2001). 'Convergence and The Effects of Spatial Interaction', Hamburg Institute of International Economics, HWWA Discussion Paper, no. 110, Hamburg.

Rey, S.J. and B.D. Montouri (1999). 'U.S. Regional Income Convergence: A Spatial Econometric Perspective', *Regional Studies*, 33, pp. 143-156.

Romer, P.M., (1986). 'Increasing returns and long run growth', *Journal of Political Economy* 94 (5), 1002–1037.

Romer, P.M., (1990). 'Endogenous Technological Change', *Journal of Political Economy* 98, 71–102.

Saldanha, Joao M. (2003). 'Pertumbuhan Regional dan Konvergensi di Indonesia', in: Mari Pangestu, Sjahrir, and Ari. A. Perdana (eds). *Indonesia dan Tantangan Ekonomi Global*, pp. 3-19. Jakarta : CSIS.

Wibisono, Yusuf. (2003). 'Konvergensi di Indonesia : Beberapa Temuan Awal dan Implikasinya', *Ekonomi dan Keuangan Indonesia, 51(1),* pp. 53-82.

Wibisono, Yusuf. (2001). Determinan Pertumbuhan Ekonomi Regional : Studi Empiris Antar Propinsi di Indonesia, *Jurnal Ekonomi Pembangunan Indonesia, 1(2),* pp. 52-83.

Vayá, E., E. López-Bazo and M. Artis (1998). 'Growth, convergence and (why not?) regional externalities?', Document de Treball de la Divisió de Ciències Jurídiques, Econòmiques i Socials, Col.lecció d'Economia, nº. E98/31, University of Barcelona

Vayá, E., E. López-Bazo, R. Moreno and J. Suriñach (2004). 'Growth and Externalities Across Economies. An Empirical Analysis using Spatial Econometrics', in: L.Anselin, R.J.G.M. Florax, and S.Rey (eds), *Advances in Spatial Econometrics: Methodology, Tools and Applications*, pp. 433-455, Springer, Berlin.

Table 1. OLS regression result for traditional absolute β-convergence equation (without spatial lag)

	The Classical Convergence Model [OLS]		The Classical Two-Club Convergence Model [OLS]	
Parameter Estimates (*p*-values in brackets)				
α	-0,159	(0,214)		
Club A			-0,065	(0,756)
Club B			-0,188	(0,392)
β	0,016	(0,122)		
Club A			-0,009	(0,603)
Club B			0,018	(0,307)
τ				
Club A				
Club B				
Time to Converge				
Annual Convergence Rate (in percent)				
Club A				
Club B				
Half Distance to the Steady State (in years)				
Club A				
Club B				
Performance Measures				
R^2	0,083		0,096	
Log. Likelihood	105,897		106,206	

Table 2. GLS regression result for traditional absolute β-convergence equation (without spatial lag)

	The Classical Convergence Model [GLS]		Two-Club Convergence Model Groupwise Heteroskedasticity [GLS]	
Parameter Estimates (*p*-values in brackets)				
α	-0,142	(0,240)		
Club A			-0,654	(0,700)
Club B			-0,188	(0,453)
β	0,014	(0,132)		
Club A			0,009	(0,519)
Club B			0,018	(0,370)
τ				
Club A				
Club B				
Time to Converge				
Annual Convergence Rate (in percent)				
Club A				
Club B				
Half Distance to the Steady State (in years)				
Club A				
Club B				
Performance Measures				
R^2	0,082		0,356	
Log. Likelihood	105,923		106,206	

Table 3. OLS regression result for spatial cross-regresive absolute β-convergence equation (with spatial lag of initial income)

	The Classical Convergence Model [OLS]		The Classical Two-Club Convergence Model [OLS]	
Parameter Estimates (*p*-values in brackets)				
α	0,066	(0,665)		
Club A			0,339	(0,159)
Club B			-0,103	(0,580)
β	-0,002	(0,866)		
Club A			-0,025	(0,200)
Club B			0,012	(0,403)
τ	**0,009**	**(0,027)**		
Club A			**0,022**	**(0,016)**
Club B			**0,020**	**(0,017)**
Time to Converge				
Annual Convergence Rate (in percent)				
Club A				
Club B				
Half Distance to the Steady State (in years)				
Club A				
Club B				
Performance Measures				
Adjusted-R^2	0,180		0,298	
Log. Likelihood	109,953		115,795	

Table 4. GLS regression result for spatial cross-regresive absolute β-convergence equation (with spatial lag of initial income)

	The Classical Convergence Model [GLS]		Two-Club Convergence Model Groupwise Heteroskedasticity [GLS]	
Parameter Estimates (*p*-values in brackets)				
α	0,137	(0,332)		
Club A			0,339	(0,032)
Club B			-0,103	(0,653)
β	-0,008	(0,484)		
Club A			**-0,024**	**(0,050)**
Club B			0,012	(0,497)
τ	**0,010**	**(0,007)**		
Club A			**0,022**	**(0,000)**
Club B			**0,020**	**(0,048)**
Time to Converge				
Annual Convergence Rate (in percent)				
Club A			**0,032**	
Club B				
Half Distance to the Steady State (in years)				
Club A			**28,533**	
Club B				
Performance Measures				
Adjusted-R^2	0,552		0,720	
Log. Likelihood	110,542		115,795	