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ISSUES IN APPLYING SPATIAL AUTOCORRELATION ON INDONESIA'S PROVINCIAL INCOME GROWTH ANALYSIS

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ABSTRACT: Research in regional growth analysis has acknowledged the importance of spatial effects as part of the analysis. Recently, there were several attempts to apply regional growth regression in Indonesia that raise the possible necessity to implement spatial effects in the growth regression. However, as the largest archipelagic country in the world, Indonesia has distinctive features in relation to spatial analysis that can hamper the application of spatial effects. The aim of this study is to investigate the necessity and the issues in applying spatial effects on Indonesia's provincial income per capita growth by introducing the spatial lag and error into the growth regression. The exercise shows the existing problems in applying spatial effects on Indonesia's regional growth regression. Moreover, the conclusion of the growth regression is hardly changed by the inclusion of spatial effects.

KEY WORDS: Spatial Autocorrelation; Growth Analysis; Regional Indonesia.

JEL CLASSIFICATION CODES: C21, C23, O18, R11

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1. INTRODUCTION

Indonesia's regional development pattern is a great analytical and policy interest. One of the policy analyses is to find the main conditions that should be developed to enhance the sub-national/regional economic condition by implementing income growth regression at a sub national level (see for example, Garcia-Garcia and Sulistianingsih, 1998; Resosudarmo and Vidyattama, 2006; McCulloch and Sjahrir, 2008; Vidyattama, 2010). While regional growth regression and analysis has been implemented in Indonesia, the question of whether spatial effect should be introduced as part of this regional growth analysis needs to be raised. This study will try to answer that particular question at the provincial level of Indonesia where the data are more reliable.

Various studies have applied spatial impacts to growth regression, including studies in the U.S., Germany, Italy, China and the European Union (Fingleton and Lopez-Bazo, 2006). However, the Indonesian regional economy is a unique candidate for spatial growth analysis. With over 17 000 islands and more than 240 million people, Indonesia is the world's largest archipelagic state by land mass and population. As an archipelagic country, the administrative regions in Indonesia often have natural barriers in the form of water boundaries that limit the interaction between two regions (Nijkamp *et al.*, 1990). Moreover, the recently rapid changes in the regional boundary within Indonesia would further hamper the implementation of spatial effect.

Recent attempts to understand income growth processes at the sub-national or regional level have resulted in the application of growth theory to regional economies, with several modifications to the regional growth model in an effort to incorporate and quantify known spatial effects (Rey and Montouri, 1999; Rey and Janikas, 2005; Fingleton and Lopez-Bazo, 2006). The spatial effects or 'neighbourhood effects' are based on the relationship between the performance of a particular region and its surrounding regions based on geographical location (Anselin, 1988), exemplified by how a neighbour's behaviour can influence the behaviour of an individual or a household (Moran, 1948). This relationship among neighbours is also called spatial autocorrelation, as the influence of a region on its neighbour will eventually affect itself.

The specific goal of this study is to investigate the necessity and the problems in implementing spatial effects on Indonesia's provincial per capita income growth. To do so, the spatial lag and spatial error are applied to standard regional growth models in order to see the significance of spatial effects and discover whether the spatial effects matter in estimating the key growth determinants. This study does not attempt to give an in-depth analysis of how and why Indonesia's provinces interact with each other.

The remainder of the paper is set out as follows. The second section discusses the growth models and the inclusion of spatial effects in a regional level analysis. The third section defines the data and variables used in this study. The fourth section discusses the two major issues in the application of spatial effects in an Indonesian growth regression. The fifth section presents the empirical growth estimation results with and without spatial effects. This will be followed by a discussion of how the results could reiterate the problem mentioned in section four and whether the spatial effects significantly change the identified growth determinants. Finally, the last section concludes the research findings.

2. REGIONAL GROWTH REGRESSION AND SPATIAL EFFECTS

The Growth Empirical Model

Literature on growth analysis often relates to the well-known Solow growth model (Romer, 2001) including the studies at regional level (Rey and Janikas, 2005). The Solow (1956) growth model, similarly proposed by Swan (1956), features a slowing down capital accumulation process that eventually ends up in steady state growth of output. In the sub national/regional analysis, this process, known as absolute convergence process, refers to the closing up of the output of those regional economies. However, there may be conditions in these economies that are the main factors causing the economic development levels (proxy by income) to differ from one another. These factors can be considered as the convergence conditioning factors and are often recognised as the determinants of the income level or the income growth (Romer, 2001). This study will focus on the issue of the impact of spatial analysis on the search for Indonesia's regional growth determinants (more discussion on the convergence process is available in Vidyattama, 2013).

Barro (1991) and Mankiw *et al*. (1992) reformulate the growth model to obtain an equation form that can be used to analyse the income growth determinants using regression techniques as applied in Sala-I-Martin (1997). In general, this regression can be expressed as:

$$\mathrm{g}y_t = \alpha + (\mathrm{e}^{\beta T} - 1)\ln y_0 + \mathbf{X}'_t\boldsymbol{\gamma}_{\mathbf{x}} + u_t \qquad (1)$$

where $\mathrm{g}y_t$ is the growth of economic output, y_0 is the initial economic output value and u_t is the error term of this estimation. The vector $\mathbf{X}'_t\boldsymbol{\gamma}_{\mathbf{x}}$ is a vector of growth determinants and its coefficients.

The Solow growth model, as it is restated by Mankiw *et al*. (1992), argues that the steady state level of output may differ across economies and depends on the physical capital saving rate or investment rate and population growth in each economy. Therefore, these two variables can constitute the matrix $\mathbf{X}'_t$ in equation (1). However, the matrix may also include other aspects of an economy that are known to affect the growth process. All these aspects are the growth determinants in the growth regression literature except for the initial income variables. The initial income can still serve as a convergence indicator in the sense of conditional convergence. This means the growth of those economies can only converge to the same balanced path if all other variables, including those individual characteristics proxied by the individual effect, are the same. In this study, this part of the modelling is not considered relevant as it puts more focus on the determinants of income growth rather than the convergence process.

Empirically, the inclusion of any possible growth determinant is important not only to search for the true determinants of growth, but also to avoid omitted variable bias (Durlauf and Quah, 1999). Omitted variable bias is an inconsistency in the estimated coefficient as a result of the exclusion of variables that have a strong correlation to both dependent and independent variables in the regression (Islam, 1995). The effort to deal with this bias has sparked the application of panel data estimation approaches. These approaches utilise regional fixed effects as well as include a time effect variable in order to capture unobservable characteristics of each economy (Islam, 1995; Caselli *et al*., 1996). This transforms equation (1) into:

$$\mathrm{g}y_{it} = \alpha + (e^{\beta T} - 1)\ln y_{i0} + \mathbf{X}'_{it}\boldsymbol{\gamma}_{\mathbf{x}} + \mathbf{T}'_{t}\boldsymbol{\gamma}_{\mathbf{t}} + \eta_i + u_{it} \quad (2)$$

where $\mathbf{T}'_t$ is the vector of time effect variable and η_i is the regional fixed effect. However, this specification may not capture the impact from neighbouring economies, which may have significant correlation with both regional economic growth and its determinants. Consequently, the estimation is still suffering from omitted variable bias. In this case, spatial econometrics is needed to recognise the existence of spatial autocorrelation.

Spatial Effects in Growth Estimation

There are several reasons to presume the existence of spatial autocorrelation in sub-national level economies. A common reason that emerges in regional studies is that the administrative boundaries used to identify regions do not necessarily reflect the boundaries of economic activities (LeSage, 1999; Rey, 2001). As a result, some economic activities within borders or across borders, such as trade and commuting, relate to the economic performance of the regions involved and hence correlate with their economic performance. The impact from the activity or input from other regions is also known as the spillover effect among locations (LeSage, 1999). Two well-known models, popularised by Anselin (1988) to acknowledge spatial dependence, are the spatial autoregressive lag model and the spatial autoregressive error model.

The spatial auto regressive lag model (SAR) assesses the connection between regions based on how each region's performance directly impacts on another. In this case, the income or growth of one region is interconnected with the other regions' income or growth. As an omitted variable can cause a biased estimation, the exclusion of spatial effects in the econometric model could change the result of the analysis (model misspecification). Therefore, the SAR model sets the impact of neighbouring regions' income to own income as the dependent variable. Following Fingleton and Lopez-Bazo (2006), the spatial auto regressive lag can be introduced to the growth regression in equation (2) as:

$$\mathrm{g}y_{it} = \alpha + (\mathrm{e}^{\beta T} - 1)\ln y_{i0} + \mathbf{X}'_{it}\boldsymbol{\gamma}_{\mathbf{x}} + \mathbf{T}'_{t}\boldsymbol{\gamma}_{\mathbf{t}} + \rho\mathbf{W}\,\mathrm{g}y_{it} + \eta_i + u_{it} \qquad (3)$$

where $\rho\mathbf{W}\,\mathrm{g}y_{it}$ is the spatial lag of the dependent variable (growth) and $\mathbf{W}$ is the spatial weight matrix.

Spatial autocorrelation can also exist in the disturbance or error term structure in the estimation, especially when the spatial autocorrelation is not directly experienced by income or growth. This is well known as the spatial autoregressive error model (SEM). The structure of the error term can also be spatially determined (Anselin, 1988) as follows:

$$u_{it} = \zeta\mathbf{W}u_{it} + \varepsilon_{it} \qquad (4)$$

or, considering the spatial multiplier effect and combined with equation (2), SEM can be written as:

$$\mathrm{g}y_{it} = \alpha + (\mathrm{e}^{\beta T} - 1)\ln y_{i0} + \mathbf{X}'_{it}\boldsymbol{\gamma}_{\mathbf{x}} + \mathbf{T}'_{t}\boldsymbol{\gamma}_{\mathbf{t}} + \eta_i + (\mathbf{I} - \zeta\mathbf{W}u_{it})^{-1}\varepsilon_{it} \qquad (5)$$

where u_{it} is the error term in the panel estimation and ε_{it} the real random factor. The main consequence of this structure in the error term is the breakdown of the homoskedasticity assumption of the estimation. The failure to achieve homoskedasticity would mean the estimated standard error of estimated parameters is incorrect. As a result, the significance of this parameter will not be measured correctly and hence, the estimates are not robust (Anselin, 1988).

To assess the necessity of including spatial effects in Indonesia's regional growth regression, the study looks at what kind of problems may occur in the implementation and then analyses the significance of spatial lag and spatial error as well as the impact of spatial effects on the key determinants of regional growth for Indonesia. The panel data estimation technique, described above in section 2, is applied to equations (3), (4) and (6) to examine these questions. The estimation is conducted using computer code for MATLAB 7.0 that is available from www.spatial-econometrics.com and discussed in Elhorst (2003).

3. DATA AND VARIABLES

This study aims to test the impact of spatial effects on various growth models. This includes the test on the model that incorporates as many variables as possible to be the candidates for growth determinants. All these models have a focus on Gross Domestic Product (GDP) per capita or Gross Regional Domestic Product (GRDP) per capita as a measure of the total net output of the economy that also represents income. Reliable data of GRDP at provincial level are available from the Regional Accounts of Indonesian Central Statistics Office (BPS) for a sufficient length of time. There are pros and contras in the use of GRDP per capita in Indonesia (Tadjoeddin *et al*., 2001; Milanovic, 2005; Hill *et al*., 2008; Akita and Lukman, 1995). However, Vidyattama (2010) has tested several alternative proxies and argues that GRDP per capita is still a better proxy in examining the growth determinants discussed below.

Investment

Investment is a growth determinant that is directly implied by the Solow growth model and the theoretical hypothesis is supported by various empirical cross-country studies that show a robust positive impact of investment on growth (Barro, 1991; Sachs and Warner, 1997). There are researches arguing that the significance of investment may not be as strong as it was first thought. Mankiw *et al*. (1992) argues that the inclusion of human capital in a growth model will reduce the significance of investment while Blomstrom *et al*. (1996) and Barro (1996) argue the direction of causality could go from economic growth to investment rather than vice versa. The weak significance of investment is also found in sub-national studies such as Ferreira (2000) for Brazil and Klump and Anh (2006) for Vietnam. Nevertheless, given the importance of investment in the theoretical model (i.e., Solow growth model), the variable should be included in this study. Data for sub-national investment in Indonesia, in terms of gross fixed capital formation, are available in the regional (provincial) income accounts by expenditure in the BPS dataset. It covers the data from 1983.

Population Growth

Population growth, another growth determinant in the Solow growth model, has been proven, for the most part, to have a negative impact on overall growth, as additional people will produce less output than the average population, given the limited capital in the economy (see for example, Mankiw *et al*., 1992; Levine and Renelt, 1992). Studies at a sub-national level have also found a negative impact of population growth on overall growth (Ferreira, 2000; Garcia-Garcia and Soelistyaningsih, 1998) and therefore, it is important for this variable to be included in the growth model. Population data for Indonesia are available from 1971, as the central statistics agency (BPS) started conducting population surveys every five years, alternating between a national census and a sample population survey.

Other Types of Capital

Along with investment and population growth, several other determinants are introduced to examine the impact of spatial autocorrelation on growth. Human capital has become a common suspected growth determinant, especially in terms of education (Mankiw *et al*., 1992; Barro and Lee, 1994). The average years of schooling of the labour force, as reported by the Indonesian Labour force survey (SAKERNAS), resembles school attainment, a standard measure of human capital popularized by Barro and Lee (1994) and will be used in this study.

Infrastructure is another factor shown to have a major impact on growth. Aschauer (1989) found that public provision of core infrastructure, such as streets, highways, airports, mass transit systems, electricity, gas, water and sewage, has a positive spillover effect on productivity. Rietveld (1989) explains the importance of infrastructure in lowering transportation costs and hence raising the connection and redistribution effect among regions. The Indonesian Ministry of Public Works has recollected data on the provincial length of roads from 1985-2005.

Other Growth Determinants

Openness is another important engine of growth since the integration of economies provides greater trade in goods and services as well as information transfer (Rivera-Batiz and Romer, 1991; Sachs and Warner, 1995). Here, the ratio of total domestic and foreign import-exports to GRDP from the BPS's regional account is utilised as a proxy of trade openness, following Amiti and Cameron (2004) at the manufacturer level.

Given their role in capital allocation, financial institutions have also been found to be an important economic factor that plays a significant role in the provincial growth process (Levine, 1999). Here, financial institutions are represented by the ratio of total savings-credit of commercial banks to GRDP. This follows one of the variables used by King and Levine (1993) to measure the importance of financial institutions. The data for Indonesia is available from the Central Bank of Indonesia. Economic structures, such as agricultural, services and manufacturing sectors, have also been found to be important growth determinants (see for example Barro and Sala-I-Martin, 1991). The inclusion of those major economic sectors means the model only leaves the non-manufacturing industry sector, including mining, as the base sector.

The dataset that will be used in the estimation consists of 26 Indonesian provinces covering 1985-2005. All data are set to be in five yearly panel databases and all growth determinant variables are five year averages. There are two reasons for having five yearly time periods. First, longer time differences capture the impact of variables that could be significant only after several years, e.g., certain kinds of physical capital and infrastructure such as schools will take several years before starting to produce educated workers and contribute to the growth process. The second reason is to eliminate the possibility of short term growth fluctuations. This data stream begins in 1985, mainly because data for investment, exports, and imports are taken from regional accounts by expenditure commencing in 1983, while the data for government investment spending and commercial banks' deposits and credits commenced in 1982 and 1985, respectively.

4. THE MAIN ISSUES IN APPLYING SPATIAL EFFECTS

Defining 'Regions'

When studying the regional economy within a country, it is common to use administrative divisions to represent each economic entity. The main reason for this is that the data is mostly recorded in these administrative divisions although it is not always demarcated to form boundaries where closely related social and economic activity takes place. There is always debate about which regional level – provincial or district – should be the basis of analysis in Indonesia (Tadjoeddin *et al*., 2001; Resosudarmo and Vidyattama, 2006). For the purposes of this study, analysis at a lower district level is not possible for a variety of reasons. First, the data series span a shorter time period and reliable district level GRDP data is only available from 1993, and does not include full expenditure data, limiting the application of growth analysis at the district level. Second, over the past two decades, the fragmentation of boundaries at the district level has proceeded more rapidly.

The use of province as the spatial unit chosen for this analysis has a major problem. Dividing the two million square kilometre land area of Indonesia into 26 provincial areas results in relatively large areas that consist of significantly diverse smaller economic areas. The large spatial unit will disguise the interaction of economic activity from spatial units within that large area. This can result in under-estimation or unidentifiable spatial patterns, depending on the size of the spatial unit chosen and available for analysis. This problem is termed the modifiable area unit problem (MAUP) (Openshaw, 1984). The MAUP is a common ailment of many spatial analyses, but unfortunately there is no easy cure. Fotheringham and Rogerson (1993) have identified that the MAUP is likely to have a significant effect on spatial analysis, which includes spatial autocorrelation (Jelinski and Wu, 1996). In addition, the number of units of observation in each year is relatively small and given that most of the provinces are not landlocked, but have a sea boundary, constructing the weight matrix to examine spatial effects will be another issue that can hamper the analysis. This will be discussed in the next sub-section.

Weighting Matrix

An essential component of the inclusion of spatial autocorrelation in growth analysis is the specification of the spatial weighting matrix. This matrix discloses the way in which differing geographies are thought to interact, illustrating the distribution of spatial relationships. There are several criteria used to determine whether an area is spatially related to another. The two most common are ‘shared boundary’ (contiguity) and ‘distance’. Cliff and Ord (1973) proposed the use of a distance decay parameter in the spatial weight matrix, recognizing that the further apart the two regions are, the less autocorrelation they have (i.e. proxy of distance). Furthermore, this distance decay factor can be combined with the length of the boundary that the two regions share, to get the more precise spatial relationship between two regions (Cliff and Ord, 1981).

Given the unique Indonesian archipelagic condition, one of the two most common spatial relationships – contiguity – is not appropriate for use in examining the impact of spatial autocorrelation on provincial economic growth in this study. The spatial weighting matrix for contiguity is represented as the binary condition of 1 if there is a common boundary and 0 otherwise. Contiguity does not include boundaries defined by sea, such as between Sumatra and Kalimantan or Sulawesi and Maluku, therefore, the application of this weighting matrix results in five provinces having no neighbour.

To replace the contiguity relationship, this study adopts the Ying (2003) approach of using a distance band to flag whether two regions are spatially related. Comparing the performance of the weighting matrix specification based on pure contiguity to the performance of the binary weight matrix based on several distance bands, Ying (2003) showed that the specification based on 2 000 kilometres was the best to capture Chinese sub-national economic spatial relationships. Following Ying, two distance band weight matrices are introduced as replacements for contiguity. The first matrix applies a distance of 200 kilometres from the land border of a particular province to determine the neighbouring status. This distance has been chosen as it is the smallest distance (to the nearest hundred) that allows all provinces to have at least one neighbour. The second matrix uses a distance band of 1 000 kilometres that has resulted in one of the provinces – Central Kalimantan – having 22 of the other 25 provinces as its neighbour. Therefore, this distance can be seen as the halfway point from the condition where no province has a neighbour to the condition where every province is a neighbour of the other 25 provinces.

The spatial weighting matrix for the other most common spatial relationship – distance – is constructed based on the geographical distance between the capital cities of two regions. Similar to Cliff and Ord (1973), this distance information will be translated to a distant decay parameter in the form of:

$$w_{ij} = \exp(-d_{ij}) \quad (6)$$

where d_{ij} is the distance between region i and region j. It has been recognised that assuming that sea distance has a similar effect on spatial relationships to that of land distance, may over-specify the relationship and decrease the significance of spatial autocorrelation (Florax and Rey, 1995).

In further developments, Case *et al*., (1993) has argued that geography may not be the only factor that determines the relationship between regions. They found that similarities between the population characteristics of the region such as ethnicity can also play a role in the economic interaction among regions and therefore, could be the basis of the weighting matrix. Following this step, three additional distinctive weighting matrices are applied in order to assess the extent of spatial autocorrelation that can be explained by these specifications. These weight matrices are not purely based on geography – migration patterns, transport costs and the Mustajab (2009) weight matrix that combines migration, transportation as well as boundary factors, are used to determine the neighbouring status. The migration pattern matrix is built based on inter-provincial migration from the 2000 population census while the transportation cost is based mostly on airline ticket fare in 2007. The immediate weakness of these static weight matrices is that the pattern of migration and transport costs in the spatial matrix should alter over time periods instead of remaining static.

5. RESULTS FROM THE APPLICATION OF SPATIAL EFFECT

The Application of Spatial Lag and Spatial Error in the Growth Regression

This study assesses the necessity of the spatial modelling in the Indonesian provincial growth regression by estimating the impact of the addition of the spatial lag and spatial error terms to the growth regression model, where the growth of each regional economy is determined by several growth determinants. As suggested by Islam (1995) and Caselli *et al*. (1996), the fixed and time effect have to be introduced in the model to ensure the robustness of this growth regression. Vidyattama (2010) argues that the introductions of fixed effects in Indonesia's regional growth regression have made neither the investment rate nor population growth significant. As discussed in section 3.1, this result is quite common in sub-national growth regression, especially in developing countries.

The main application of growth regression is to search for the robust determinants of growth, so that these may be nurtured and cultivated by policy makers and others with a strong interest in the growth of an area. Therefore, it is necessary to include any possible growth determinants that are available and reliable. Given this, human capital, infrastructure, openness, financial institution and economic structure are introduced in the equation (see sections 3.1 to 3.4 for justification of inclusion of these variables). As the inclusion of regional fixed and time effects variables is also important, the estimation will be based on equation (4) with

$$\mathbf{X}'_{it}\boldsymbol{\gamma}_{\mathbf{x}} = \gamma_3\ln(s)_{it} + \gamma_{4a}\ln(p)_{it} + \gamma_{4b}\ln(p)_{it-5} + \gamma_5\ln(ysch)_{it} + \gamma_6\ln(rdpc)_{it} + \gamma_7\ln(trds)_{it} + \gamma_8\ln(fs)_{it} + \gamma_9\ln(agrs)_{it} + \gamma_{10}\ln(serv)_{it} + \gamma_{11}\ln(manu)_{it} \quad (7)$$

where :

$ysch_{it}$	is the average number of years of schooling of the total population above 10 years of age at time t to represent the stock of human capital (years)
$rdpc_{it}$	is the length of roads per population to represent infrastructure (km/population) in province i at time t
$trds_{it}$	is the ratio of total trade (exports plus imports) to total GRDP to represent openness in province i at time t.
fs_{it}	is the ratio of total deposits and credits in commercial banks to total GRDP to represent the size of financial institutions in province i at time t.

agrs_{it}	is the ratio of the agriculture sector value added to total GRDP in province i at time t.
serv_{it}	is the ratio of the services sector value added to total GRDP in province i at time t.
manu_{it}	is the ratio of the manufacturing sector value added to total GRDP in province i at time t.

With an adjusted R^2 of 73.3 percent, the results of the growth estimation show that the additional growth determinant variables in equation (7) add important value to the estimation. Without the inclusion of spatial autocorrelation, it indicates that road infrastructure and openness are positive growth determinants while the provinces with large service sectors are growing significantly more slowly than the provinces with large non-manufacturing industries. For most Indonesian provinces, this reflects the differences between the provinces that are heavily reliant on the government sector and the provinces with a sizeable mining sector.

The introduction of spatial lag into the model has a noticeable but not major impact on this growth regression (Table 1). The spatial lag based on the 1 000 kilometres distance band is the only lag that is significant at the 1 percent significance level. While the lag based on distance is still significant at the 10 percent significance level, the spatial lag based on 200 kilometres is not. The introduction of the former two spatial lags does not change the conclusion of the model. All of the three significant factors mentioned above – road infrastructure, openness, and service sector size – are unchanged in terms of significance. Moreover, only the adjusted R^2 of the estimation using the 1 000 kilometres distance band is higher that the adjusted R^2 of the model without spatial lag.

Table 1. Panel Growth Regression with and without spatial lag, 1985-2005.

	non spatial		Distance		200Km Distance band		1 000Km Distance band	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Ln y_{it-5}	-0.811^{***}	-9.024	-0.777^{***}	-10.357	-0.784^{***}	-10.477	-0.751^{***}	-10.138
Ln s_{it}	-0.025	-0.535	-0.030	-0.791	-0.026	-0.676	-0.023	-0.621
Ln pop_{it}	-0.391	-1.572	-0.380^{*}	-1.869	-0.380^{*}	-1.859	-0.366^{*}	-1.846
Ln pop_{it-5}	-0.042	-0.172	0.005	0.025	0.001	0.003	-0.024	-0.124
Ln $ysch_{it}$	0.173	1.333	0.135	1.244	0.143	1.329	0.098	0.942
Ln $rdpc_{it}$	0.127^{**}	2.116	0.132^{***}	2.710	0.134^{***}	2.729	0.121^{**}	2.546
Ln $trds_{it}$	0.087^{**}	2.108	0.076^{**}	2.235	0.075^{**}	2.198	0.064^{*}	1.927
Ln $agrs_{it}$	-0.083	-1.342	-0.077	-1.521	-0.079	-1.551	-0.073	-1.479
Ln $servs_{it}$	-0.640^{***}	-5.153	-0.609^{***}	-6.004	-0.630^{***}	-6.186	-0.571^{***}	-5.702
Ln $manu_{it}$	-0.061	-1.169	-0.050	-1.179	-0.052	-1.226	-0.045	-1.082
Ln fs_{it}	0.019	0.531	0.018	0.608	0.019	0.645	0.010	0.342
W.Ln y_{it}			-0.191^{*}	-1.842	-0.133	-1.495	-0.684^{***}	-2.826
adj. R^2	0.733		0.723		0.721		0.737	
Log likelihood	157.296		158.527		158.187		160.960	

Note: *, **, and *** are 10%, 5%, and 1% significance, respectively. Coef. = Coefficient, t-stat.= t statistics. Source: the Author.

Unlike the spatial lag, the spatial error based on the 1 000 kilometres distance band is not significant, while the other two specifications are significant at the 10 percent significance level. As in the spatial lag model, the significance of the three variables – road infrastructure, openness, and service sector size – that have been identified as significant growth determinants is maintained. As the standard error fell, the agriculture sector size has become negatively significant. However, the main drawback of the inclusion of a spatial error term is that all the adjusted R^2 are now lower than the model without spatial error or spatial lag (Table 2).

It can be summarised that in the growth regression that includes various growth determinants, the spatial lag based on a 1 000 kilometres distance band is the only spatial effect that produces a higher accuracy based on adjusted R^2 compared to the model without spatial effects. This strengthens the result that only spatial lag based on 1 000 kilometres has a strongly significant impact on provincial growth in Indonesia. The R^2 also indicates that the other spatial effect additions in the regression may cost the degrees of freedom more than the additional information they add. This could be because the additional information has been covered by the additional growth determinants as well as fixed and time effects.

Table 2. Panel Growth Regression with and without spatial error, 1985-2005.

	non spatial		Distance		200Km Distance band		1 000Km Distance band	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Ln $y_{it\text{-}5}$	-0.811***	-9.024	-0.793***	10.544	-0.798***	-10.619	-0.797***	-10.668
Ln s_{it}	-0.025	-0.535	-0.028	-0.727	-0.023	-0.611	-0.024	-0.612
Ln pop_{it}	-0.391	-1.572	-0.359*	-1.787	-0.393*	-1.937	-0.344*	-1.669
Ln $pop_{it\text{-}5}$	-0.042	-0.172	-0.017	-0.088	-0.010	-0.052	-0.075	-0.369
Ln $ysch_{it}$	0.173	1.333	0.203*	1.950	0.173*	1.658	0.162	1.534
Ln $rdpc_{it}$	0.127**	2.116	0.143***	2.901	0.138***	2.785	0.133***	2.652
Ln $trds_{it}$	0.087**	2.108	0.072**	2.078	0.068*	1.948	0.078**	2.231
Ln $agrs_{it}$	-0.083	-1.342	-0.089*	-1.778	-0.086*	-1.745	-0.087*	-1.727
Ln $servs_{it}$	-0.640***	-5.153	-0.579***	-5.566	-0.605***	-5.832	-0.619***	-5.952
Ln $manu_{it}$	-0.061	-1.169	-0.044	-1.049	-0.049	-1.155	-0.056	-1.288
Ln fs_{it}	0.019	0.531	0.010	0.352	0.020	0.649	0.013	0.439
W.u_{it}			-0.241*	-1.938	-0.168*	-1.668	-0.262	-1.072
adj. R^2	0.733		0.727		0.725		0.721	
Log likelihood	157.296		158.429		158.124		157.641	

Note: *, **, and *** are 10%, 5%, and 1% significance, respectively. Coef. = Coefficient, t-stat.= t statistics. Source: the Author.

Spatial Negative Autocorrelation and the Issues in its Application

One debatable result from Tables 1 and 2 is the finding of negative spatial autocorrelation in the growth regression when a time fixed variable is introduced. There is a view that a negative spatial lag coefficient observed may be a result of bias, which is caused by a problem in the spatial unit used (provinces) (Smith, 2001). On the other hand, there is another view arguing that it is the misspecification in the estimation process that may actually hide the negative spatial autocorrelation (Griffith, 2006).

The latter argument could be accepted as the time effect may capture the fluctuation of Indonesia's economy during 1985-2005 that drove the provinces to grow in similar patterns and hence, have misleading positive autocorrelation. Therefore, including the time effect will reveal the existence of underlying negative spatial autocorrelation. Moreover in the case of Indonesia, it has been argued that the provinces within Java, especially Jakarta, may have absorbed the financial and human capital resources from other provinces in Indonesia (Hill *et al.*, 2008). Therefore, the existence of negative spatial autocorrelation in Indonesia can be justified.

The former argument that negative spatial autocorrelation is a sign of bias from an aggregation problem in the spatial unit used also has firm ground. Smith (2001) shows that in the case that most of the interaction occurs within the spatial unit, the standard maximum likelihood process would not only underestimate the existence of spatial interaction into zero, but is also likely to favour the existence of negative spatial autocorrelation, especially when the sample is small. Unfortunately, this symptom is a correct description of the issue that is raised when using provincial level data to analyse spatial autocorrelation. It is more likely that the interaction is happening between district levels rather than provincial levels and the aggregation to provincial level has made the number of observations very small. Furthermore, the spatial lag based on a 1 000 kilometres distance band is identified to be the most significant spatial effect. The use of this spatial weight matrix has made the region seemingly even larger and hence, showing more significant negative spatial autocorrelation. Therefore, it can be concluded that although there is an argument for why the spatial autocorrelation in Indonesia's regional growth results have a negative sign for spatial effects, the arguments that support the existence of bias due to the selection of the spatial unit are stronger.

Is the Impact on Growth Determinants Significant?

The question of whether the spatial effect has affected the growth regression cannot be answered only by looking at the significance of spatial autocorrelation. The significance of its impact on the growth determinants used in the equations must also be considered. This is done by examining whether the changes in the indicated growth determinants coefficient is significant by conducting a t-test of

$$\gamma_{3\text{non-spatial}} = \gamma_{3\text{spatial}},\ \gamma_{4a\text{non-spatial}} = \gamma_{4a\text{spatial}},\ \text{and}\ \gamma_{4b\text{non-spatial}} = \gamma_{4b\text{spatial}}.$$

The spatial lag and error have different significance of impact on the growth determinants. Table 3 shows the changes in the magnitude of the growth determinants' coefficients and reveals that the inclusion of spatial lag significantly lowers the impact of school attainment and trade. This means that schooling and trade have stronger impacts on growth because of the neighbouring effect. While the interpretation of the result on trade is obvious, the result regarding school attainment may have to be linked with the migration or commuting pattern of people with higher education. The contribution of services and manufacturing sectors are also affected by the spatial lag based on distance and a 1 000 kilometres distance band. Meanwhile, trade, services and manufacturing sectors are significantly affected by the inclusion of spatial error based on distance and a 200 kilometres distance band. Although none of the growth determinants are affected in the inclusion of spatial error based on a 1 000 kilometres distance band, the other results show that spatial autocorrelation does have an impact on growth regression.

Table 3. The changes in coefficient as a result of spatial effect inclusion in panel growth regression.

Estimation type	Coef.	Spatial Lag model			Spatial Error Model		
		Distance	200Km Distance Band	1 000Km Distance Band	Distance	200Km Distance Band	1 000Km Distance Band
Fixed effect, Time period	Ln $y_{it\text{-}5}$	0.034^{***}	0.027^{**}	0.060^{***}	0.018	0.013	0.014
	Ln s_{it}	-0.005	-0.001	0.002	-0.003	0.002	0.001
	Ln pop_{it}	0.011	0.011	0.025	0.032	-0.002	0.047
	Ln $pop_{it\text{-}5}$	0.047	0.043	0.018	0.025	0.032	-0.033
	Ln $ysch_{it}$	-0.038^{**}	-0.030^{*}	-0.075^{***}	0.030^{*}	0.000	-0.011
	Ln $rdpc_{it}$	0.005	0.007	-0.006	0.016^{**}	0.011	0.006
	Ln $trds_{it}$	-0.011^{**}	-0.012^{**}	-0.023^{***}	-0.015^{***}	-0.019^{***}	-0.009
	Ln $agrs_{it}$	0.006	0.004	0.010	-0.006	-0.003	-0.004
	Ln $servs_{it}$	0.031^{**}	0.010	0.069^{***}	0.061^{***}	0.035^{**}	0.021
	Ln $manu_{it}$	0.011^{*}	0.009	0.016^{**}	0.017^{***}	0.012^{*}	0.005
	Ln fs_{it}	-0.001	0.000	-0.009^{**}	-0.009^{**}	0.001	-0.006

Note: *, **, and *** are 10%, 5%, and 1% significance, respectively. Coef. = Coefficient. Source: the Author.

Other Weight Matrix Specifications

As discussed in section 3, the specification of the spatial weighting matrix may hamper the significance of spatial autocorrelation in growth analysis among provinces in Indonesia. So far, three spatial weight matrices have been applied in this analysis. Several other weight matrix specifications that are not necessarily based on spatial information have been experimented with, including transportation costs, migration based on the place of residence five years before and the combination of transport, migration and the border that has been built by Mustajab (2009).

The results from the inclusion of the additional weighting matrices into the growth regression are shown in Table 4 and 5. These show that none of the matrices are significant for either the lag or error term. Furthermore, none of the coefficients is considerably changed by the inclusion of the weighting matrix.

Table 4. Panel Growth Regression with and without other alternative lag, 1985-2005.

	non spatial		Transport Cost		Migration		Mustajab (2009)	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Ln y_{it-5}	-0.811***	-9.024	-0.795***	-10.736	-0.809***	-10.831	-0.805***	-10.817
Ln s_{it}	-0.025	-0.535	-0.030	-0.784	-0.025	-0.664	-0.027	-0.702
Ln pop_{it}	-0.391	-1.572	-0.387*	-1.899	-0.388*	-1.884	-0.385*	-1.866
Ln pop_{it-5}	-0.042	-0.172	-0.018	-0.089	-0.044	-0.219	-0.036	-0.182
Ln $ysch_{it}$	0.173	1.333	0.155	1.448	0.170	1.571	0.165	1.511
Ln $rdpc_{it}$	0.127**	2.116	0.130***	2.656	0.127**	2.552	0.129***	2.600
Ln $trds_{it}$	0.087**	2.108	0.084**	2.466	0.087**	2.529	0.085**	2.481
Ln $agrs_{it}$	-0.083	-1.342	-0.075	-1.464	-0.081	-1.574	-0.082	-1.591
Ln $servs_{it}$	-0.640***	-5.153	-0.630***	-6.182	-0.641***	-6.222	-0.636***	-6.179
Ln $manu_{it}$	-0.061	-1.169	-0.053	-1.232	-0.059	-1.382	-0.060	-1.395
Ln fs_{it}	0.019	0.531	0.016	0.532	0.019	0.637	0.019	0.653
W.Ln y_{it}			-0.349	-1.477	-0.029	-0.195	-0.043	-0.487
adj. R^2	0.733		0.721		0.716		0.716	
Log likelihood	157.296		158.090		157.300		157.390	

Note: *, **, and *** are 10%, 5%, and 1% significance, respectively. Coef. = Coefficient, t-stat.= t statistics. Source: the Author.

Table 5. Panel Growth Regression with and without other alternative error, 1985-2005.

	non spatial		Transport Cost		Migration		Mustajab (2009)	
Variable	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Ln y_{it-5}	-0.811***	-9.024	-0.805***	-10.770	-0.811***	-10.899	-0.807***	-10.833
Ln s_{it}	-0.025	-0.535	-0.028	-0.729	-0.028	-0.714	-0.027	-0.714
Ln pop_{it}	-0.391	-1.572	-0.384*	-1.862	-0.371*	-1.792	-0.387*	-1.879
Ln pop_{it-5}	-0.042	-0.172	-0.039	-0.195	-0.053	-0.263	-0.034	-0.170
Ln $ysch_{it}$	0.173	1.333	0.181*	1.699	0.187*	1.760	0.180*	1.689
Ln $rdpc_{it}$	0.127**	2.116	0.133***	2.647	0.137***	2.780	0.130***	2.617
Ln $trds_{it}$	0.087**	2.108	0.084**	2.408	0.084**	2.424	0.087**	2.508
Ln $agrs_{it}$	-0.083	-1.342	-0.081	-1.594	-0.075	-1.479	-0.084*	-1.657
Ln $servs_{it}$	-0.640***	-5.153	-0.633***	-6.092	-0.636***	-6.171	-0.627***	-6.089
Ln $manu_{it}$	-0.061	-1.169	-0.059	-1.366	-0.058	-1.352	-0.060	-1.398
Ln fs_{it}	0.019	0.531	0.019	0.627	0.023	0.780	0.018	0.591
W.u_{it}			-0.230	-0.902	-0.162	-1.036	-0.040	-0.396
adj. R^2	0.733		0.721		0.721		0.719	
Log likelihood	157.296		157.575		157.581		157.347	

Note: *, **, and *** are 10%, 5%, and 1% significance, respectively. Coef. = Coefficient, t-stat.= t statistics. Source: the Author.

6. CONCLUSION

Recently, several attempts to understand the growth process at the sub-national or regional level have been carried out by applying growth regression on Indonesia's provincial level economy. In doing so, a question regarding the necessity of adapting spatial effects into Indonesia's provincial growth regression was raised. Nevertheless, the analysis needs to take account of Indonesia's distinctive feature as an archipelagic country, which has created some issues in the implementation of spatial effects application. The archipelagic condition means the administrative regions may have natural barriers in the form of water boundaries that can limit interaction between two regions. As a result, traditional contiguity is not appropriate for use as a spatial weighting matrix. Instead, two spatial specifications –200 kilometres and 1 000 kilometres distance bands – are used to replace contiguity. In addition, the weighting matrices that are based on interactions such as the pattern of migration and transport costs are assessed as alternatives to spatial weight matrices.

The inclusion of a spatial lag and spatial error terms based on the three spatial specifications is shown to have some impact on growth at a provincial level. However, the impact becomes insignificant when the other available growth determinants are introduced. The spatial lag based on the 1 000 kilometre distance band is the exception, producing a significant spatial lag coefficient. Nevertheless, the negative sign of the coefficient creates suspicion that the result has been affected by the problems in the spatial unit used, especially given the large area of provinces this would not give the correct representation of how economic regions interact with each other in Indonesia. Nevertheless, the introduction of other weighting matrices does not show significant differences in the regression result.

The specific goal of this research was to investigate the necessity of spatial effects as well as the problems in their application on Indonesia's provincial growth determinants estimation. The results show that the impact of introducing spatial autocorrelation is insignificant in Indonesia's provincial case when the growth regression has already included various growth determinants along with fixed and time effects. From all the specifications used in this study only the spatial lag based on a 1 000 kilometres distance band still had significant information to be added to the growth model.

Ironically, the coefficient of this specification of spatial effect is negatively significant prompting the potential problem in the estimation.

This means that while spatial effects may play a role in Indonesia's regional growth, the size of provinces, the topography of Indonesia's archipelago state and the low number of observations (26 provinces) has made it difficult for the application of spatial effects to come out with a sensible result. Nevertheless, Sandee (2013) indicates that there is still an ongoing problem with the connectivity among islands in Indonesia, and Hill *et al*. (2008) shows that Jakarta as a capital city has dominated the overall growth and affected other regional growth in Indonesia. The latter prompts further research regarding spatial effects in Indonesia's regional growth including the distance to the capital city (Gallup *et al*., 1999) or geographical position (Kim and Law, 2012).

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