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Does Investment and Energy Infrastructure Influence Convergence in Sumatra Island, Indonesia?

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ABSTRACT

This research aims to prove the existence of a convergence process and analyse the effect of investment and energy infrastructure on the convergence process on Sumatra Island by including the element of space to understand spatial convergence better. The dataset used in panel data consists of 154 regions (district/municipality) from 2010 to 2020. The analytical tools used with a spatial econometric approach consist of Spatial Autoregressive and Spatial Error Model. The results of the convergence test prove that there is convergence in both absolute and conditional convergence, and there is a difference in the speed of convergence for the two equations. Meanwhile, the results of the spatial approach state that there are spatial dependencies so that neighbouring regions influence the region. The estimation results of conditional β-convergence reveal that investment and government spending in infrastructure has a positive and significant effect, in contrast to energy infrastructure, which has a negative and significant relationship, and only human capital is not significant to the convergence process in Sumatra.

Keywords: Convergence, Energy Infrastructure, Investment, Spatial Panel Data, Sumatra
JEL Classifications: C33, D63, H54, Q43, R11

1. INTRODUCTION

Inequality between regions is the difference in development occurring at various levels between states, provinces and districts, and rural and urban areas. Inequality between regions affects the incidence of civil conflict; countries with higher income inequality tend to experience internal violence (Ezcurra, 2019). Too long of inequality can trigger internal conflict (Lessmann, 2016). It makes the issue of inequality between regions important in the economic theory literature and attracts the attention of many researchers.

The phenomenon of inequality development between regions in Indonesia is a significant concern considering regional inequalities that continue to occur and trigger crime rates, for example, cases in the provinces of Aceh, Riau, East Kalimantan, and Papua (Tadjoeddin et al., 2001; 2020). Furthermore, two of these areas are located on Sumatra Island. This island is Indonesia's second region with rapid development. It has a strategic location located in the Malacca Strait. The province on this island produces a variety of natural resources such as oil and gas producers, various mineral mines, and oil palm plantations. According to Sjafrizal (2018), the difference in ownership of natural resources is one of the causes of economic inequality between regions.

Sumatra's average provincial economic growth rate for the 2011-2020 period was 4.46%, indicating positive economic growth. Meanwhile, the income distribution based on the Gini ratio shows a downward trend from 0.342 to 0.319. Moreover, income inequality is generally because the index value is bigger than 0.300. Based on the neoclassical hypothesis that at the beginning of development, developing countries experienced divergence conditions, namely increasing inequality between regions, and as development continued to develop, the conditions that occurred were convergence (Sjafrizal, 2018), so the existing data indicated a convergence process.

According to Shankar and Shah (2003), the calculation of regional inequality with a dynamic concept is based on the Solow economic growth model, commonly called sigma and beta convergence. The concept of convergence uses the assumption of a diminishing return to capital, referring to a long-term process in which the GDP per capita of poor regions grows faster than rich regions (Barro and Sala-i-Martin, 1992). In this case, catch-up will eventually become convergence, or the GDP per capita between regions will be the same in steady-state conditions (Sala-i-Martin, 1996).

The latest empirical results related to convergence from outside Indonesia are results that state there is convergence, including in Europe by Kubis and Schneider (2016); Butkus et al. (2018); Alexa et al. (2019); Dogan and Kındap (2019); Balash et al. (2020); Montresor et al. (2020); Postiglione et al. (2020); Demidova, (2021). In America by Yu and Lee (2012); Breau and Saillant (2016); Flores-Chamba et al. (2019); Leiva and Pino (2020); Aristizábal and García (2021), in Asia by Barro (2016); Lee (2016; 2017); Zhang et al. (2019); (Mendez and Santos-Marquez, 2020). On the other hand, the results suggest a divergence by Goschin (2014; 2017), Simionescu (2014), Pietrzykowski (2019) in Europe, Lolayekar and Mukhopadhyay (2017; 2019) in Asia, and Kant (2019) in Africa. Meanwhile, empirical results in Indonesia state that there is a convergence by Maryaningsih et al. (2014); Rahayu et al. (2015); Wau et al. (2016); Kurniawan et al. (2019); Mendez (2020); Aginta et al. (2021), and which states the divergence by Firdaus and Rindayati (2012). The difference in the inconsistent empirical results creates a gap for us to examining the convergence process.

Furthermore, convergence analysis using new spatial elements was developed and pioneered by Rey and Montouri (1999) and continues to develop until now. According to Capello and Nijkamp (2009), analysing economic inequality using spatial elements will be much more realistic than without spatial elements. Research in Indonesia that examines interregional convergence with spatial aspects in terms of spatial-econometrics is still few. Our knowledge of those who conducted studies, including by Vidyattama (2013), Aritenang (2014), and Aspiansyah and Damayanti (2019), specifically for the Sumatra Island, have not yet been conducted.

In this paper, our research objective is to reveal the influence of investment and energy infrastructure on the convergence process in Sumatra Island on a regional scale to understand spatial convergence better. This paper is structured as follows: the next section on theoretical concepts and a brief review of the research carried out on the subject. The following section explains the data and methodology, and the fourth section presents and explains the empirical results. The final section presents the conclusions and policy implications.

2. LITERATURE REVIEW

The theoretical framework in this paper begins with a neo-classical hypothesis based on the theory of equalisation of remuneration factors production between regions by Borts (1960), which is a continuation of the neo-classical regional economic growth theory proposed by North (1955). This hypothesis shows that inter-regional inequality tends to be higher while inequality will be lower in developed countries. In addition, it can also be estimated that in developing countries, inequality increases or divergence, but the more advanced the development of a country, there will be a process of decreasing the level of inequality between regions or convergence. The proof of this hypothesis has been tested by Williamson (1965) through a study in developed and developing countries using time series and cross-section data. The results state that the hypothesis is empirically proven.

According to Barro and Sala-I-Martin (1991), there are two concepts of convergence. First, β-convergence is a catch-up process for the economy of poor regions is faster than the economy of rich regions. In the long term, the level of income per capita between regions will be the same in steady-state conditions. Second, σ-convergence, namely the occurrence of a decrease in economic inequality from time to time, means that convergence occurs if the dispersion, measured by the standard deviation, is the logarithm of per capita income between regions over time. β-convergence tends to produce σ-convergence, but factors that increase inequality offset this process. Therefore, β-convergence is not always synonymous with σ-convergence (Barro and Sala-i-Martin, 2004).

The convergence regression model was developed by Barro and Sala-i-Martin (1990). This model produces coefficients on the initial condition variable commonly called β-convergence and measures convergence speed. A negative coefficient value indicates convergence and otherwise describes a divergence condition. Furthermore, the β-convergence model was further improved by Barro (1991) and Barro and Sala-i-Martin (1992) by bringing the idea that poor and rich economies may not converge at the same steady-state condition. They categorise convergence towards the same steady-state condition as absolute convergence and towards a different steady-state condition as conditional convergence. They argue that the expected negative relationship between initial per capita income levels and growth rates holds when structural differences between poor and rich economies are constant.

Furthermore, the convergence analysis by including spatial elements pioneered by Rey and Montouri (1999) in the US period 1929-1994 stated a strong global and local spatial autocorrelation pattern. Moreover, the development by Rey (2001) found that geographical factors were not a determinant of changes in income distribution between regions, and the distribution of mobility that fluctuated across states was sensitive to the position of adjacent regions in the same distribution.

Furthermore, the latest research on the application and development of spatial convergence is carried out with different regional analysis units, including by Sanso-Navarro et al. (2020) across countries worldwide, Yu and Lee (2012) in the United States, Breau and Saillant (2016) in Canada, Aristizábal and García (2021) in Columbia, Flores-Chamba et al. (2019) in Ecuador, Leiva and Pino (2020) in Chile, Lima and Neto (2016) in Brazil, Alexa et al. (2019); Balash et al. (2020); Montresor et al. (2020); Panzera and Postiglione (2021); Pietrzykowski (2019); Postiglione et al. (2020) in the European Union region, Yildirim et al. (2009); Dogan and Kındap (2019) in Turkey, Goschin (2017) in Romania, Sun et al. (2017) in China, Chatterjee (2017) in India, Mendez and Santos-Marquez (2020) in the ASEAN region, and Indonesia by Vidyattama (2013); Aritenang (2014); Aspiansyah and Damayanti (2019). Empirical results show that geographically weighted regression increases the model's better explanatory power. There is considerable variation in convergence speed, which traditional convergence analysis cannot capture.

In conditional β-convergence, several control variables support the convergence process. Based on the conditional β-convergence above, some previous studies support our research. Balash et al. (2020) research evidence that investment affected Russia's convergence process from 2010 to 2014. The results of spatial autocorrelation suggest that the role of territorial proximity affects interregional convergence. Furthermore, in the same region, Demidova (2021) found a β-convergence only for the middle and rich regions from 2000 to 2017. Poor areas are not growing faster than other regions, confirming the relevance of spatial development strategies. The convergence process of rich regions can be achieved by increasing investment and reducing investment risk. However, investment in poor and middle-income areas is not practical. Meanwhile, poor and middle-income regions receive positive spillovers from the growth of neighbouring regions. It is possible to expect a reduction in the difference in living standards between poor and rich regions.

The article by Gömleksiz et al. (2017) found that investment was positive and significant to the convergence process that occurred in Turkey. Furthermore, Barro (2015) reveals that the investment ratio has a positive and significant effect on convergence. Meanwhile, human capital as a proxy for girls' and boys' average years of schooling produces different results. Women have insignificant positive scores, and men have significant negative values. A plausible interpretation is that expanding women's achievements relative to men signifies a more general improvement in the political and social arrangements that support economic growth.

A seminal paper by Mankiw et al. (1992) or MRW pioneered the relationship between physical and human capital in the mechanism of economic growth. They state that the output of an economy is influenced by a combination of physical capital and labour skills and that the accumulation of human capital occurs and the accumulation of physical capital. The MRW model is a development of the Solow (1956) growth model or Augmented Solow. An essential assumption of the Solow Augmented model is that the accumulation of human capital is the time devoted by individuals to acquire new skills, not work. Lima and Neto's (2016) study using the MRW model with spatial extension reveals a strong spatial dependence among Brazil's micro-regions and significant investment in physical capital and human resources in supporting the convergence process.

Empirical results by Lee (2016) state that human capital proxied from the average school-age and squared has a significant effect. Educational attainment shows that the growth rate increases with the educational attainment rate only when the country has reached 6.0 years of schooling, which is the threshold level. Similar results were proved by Lee (2017) in China. Furthermore, Lee (2020) proves that human capital and investment are not significant to the convergence of middle-income trap countries.

Zhang et al. (2019) found that human capital affects convergence in China. Furthermore, the positive "underdevelopment benefits" due to lower initial income are almost outweighed by the negative impact of low levels of human capital in poor areas. Meanwhile, Yang et al. (2016) results in China for 1997-2006 found that investment in fixed assets, government spending on education and health as a proxy for human capital, and infrastructure development positively affected regional convergence.

Empirical results by Leiva and Pino (2020) specifically show that improving educational performance in the early stages of primary school can reduce disparities in the long term while supporting the convergence process. In the paper by Rahayu et al. (2015), human capital proxies from government spending on education significantly affect the convergence process in Kalimantan. Furthermore, the empirical results from Aspiansyah and Damayanti (2019) with the MRW spatial model prove that human capital has a significant positive relationship to the convergence process.

Flores-Chamba et al. (2019) emphasise increasing public spending on productive infrastructure to support the provincial convergence process. Moreover, the results reveal that convergence speed varies according to the method used; in the "conventional" method, the speed is close to 2%. The Spatial Durbin Model is about 43%. This shows that including an autoregressive process from the dependent variable results in a more "relevant" and "efficient" convergence estimate. Hooper et al. (2018; 2020) prove that increasing infrastructure spending on roads and higher education in a given decade can reduce the gaps and thus help the convergence process. Furthermore, Fageda and Olivieri (2019) proves the convergence process in Spain and finds that road infrastructure positively impacts the convergence process.

Empirical results by Chatterjee (2017) in India prove that one of the drivers of the convergence process is electricity infrastructure. Research by Firdaus and Rindayati (2012) resulted in several factors that affect regional income inequality in Java, including health infrastructure, availability of electricity and clean water. Meanwhile, the empirical results by Maryaningsih et al. (2014) emphasised the availability of basic infrastructure, including land and sea transportation and electricity, to convergence in Indonesia, thus making it an important condition for achieving sustainable growth. Furthermore, Hidayat et al. (2020) study revealed that balanced funds and energy infrastructure significantly reduce inequality.

3. METHODOLOGY

In this paper, a quantitative method relates to the calculated value analysed from the use of spatial econometrics to explore the convergence process at a regional scale. The area that becomes the unit of analysis is the regencies/municipalities in Sumatra, totalling 154. The time-series data used are from 2010 to 2020. Data sources come from several surveys from Statistics Indonesia (BPS), including socio-economic surveys, labour force surveys, population censuses, GRDP, and public finances.

In simple terms, the β-convergence model is absolute if the model only includes the initial condition variable as the independent variable without any control variables. Meanwhile, if there is a control variable in the model, the resulting β-convergence model is conditional. Next, the stages of our research start from beta testing absolute convergence, which refers to previous research, including by Barro and Sala-i-Martin (1992); Alexiadis (2013); Dogan and Kındap (2019). The form of the equation is as follows:

$$\log Y_{i,t} - \log Y_{i,t-1} = \alpha - \beta_1 \log Y_{i,t-1} + u_{i,t} \quad (1)$$

Where $Y_{j',t}$ is GRDP per capita district/city i in year t, $Y_{i,t-1}$ is GRDP per capita district/city i in the previous year, α is a constant, β_1 is the regression coefficient, and $u_{i,t}$ are residuals.

Convergence conditions occur if the β_1 coefficient is negative. Otherwise, if the β_1 coefficient is positive, the divergence condition occurs. The coefficient of β_1 can be expressed as follows:

$$\beta_1 = -\left(1 - e^{-\beta T}\right) \quad (2)$$

Where T is the analysis period, the speed of convergence between regions to achieve economic equity under steady-state conditions over a certain period can be calculated as follows:

$$\beta = -\frac{\ln(\beta_1 + 1)}{T} \quad (3)$$

In addition, another indicator to characterise the speed of convergence is the half-life time (τ), which is defined as the period required to eliminate half of the initial inequality. The value of half-life time can be calculated by the following equation: (Arbia, 2006)

$$\tau_{half-life} = \frac{\ln(2)}{\beta} = 0.693147\beta^{-1} \quad (4)$$

The second stage is testing conditional β-convergence by adding control variables. The control variables used in this research model include investment, government spending on infrastructure, energy infrastructure, and human capital. The selection of these variables is based on theory, and previous research carried out in various places.

Furthermore, the conditional β-convergence model equation becomes as follows:

$$\log Y_{i,t} - \log Y_{i,t-1} = \alpha - \beta_1 \log Y_{i,t-1} + \beta_2 \log INV_{i,t} + \beta_3 \log BL_{i,t} + \beta_4 EI_{i,t} + \beta_5 HC_{i,t} + u_{i,t} \quad (5)$$

The operational variable is defined from equation (5): INV is an investment, a proxy from gross fixed capital formation or government investment in million rupiahs. For BL, it is a proxy for government spending on infrastructure in units of thousands of rupiah. The EI variable is the energy infrastructure proxy for the household electrification ratio, indicating household access to electricity. HC is human capital, proxied from senior high school participation rate (SMA/equivalent).

2.1. Spatial Panel Data

The linear regression model on panel data that has a specific spatial effect without the effect of spatial interaction, according to Elhorst (2003), is stated in the following equation:

$$y_{it} = X_{it}\beta + \mu_i + \varepsilon_{it} \quad (6)$$

where i is the index for the cross-sectional dimension (spatial unit) where i=1,…, N. t is the time dimension where t=1,…,T. y_{it} is the observation unit on the dependent variable on the data i and time t. X_{it} shows the observation vector of the independent variable at the spatial unit i and time t (1, K). β parameter vector (K,1), and ε_{it} are independent and identically distributed errors for each i and t with mean 0 and variance σ^2. μ_i is a spatial specific effect.

The linear regression model of panel data with a specific interaction between spatial units will have a dependent variable spatial lag or spatial process on error, usually referred to as the spatial lag model and the spatial error model (SEM) (Elhorst, 2014). The spatial lag model states that the dependent variable depends on the neighbouring dependent variable and one of the local characteristics. The following is the equation for the spatial lag model or Spatial Autoregressive (SAR):

$$y_{it} = \rho \sum_{j=1}^{N} W_{ij} y_{jt} + x_{it}\beta + \mu_i + \varepsilon_{it} \quad (7)$$

Where ρ is the SARcoefficient, and $\boldsymbol{W}_{ij}$ is the element of the spatial weighting matrix (***W***).

The SEM states that the dependent variable depends on local characteristics and the correlation error between spaces. The following is the form of the equation for the SEM:

$$y_{it} = X_{it}\beta + \mu_i + \phi_{it} \quad (8)$$

$$\phi_{it} = \lambda \sum_{j=1}^{N} W_{ij}\phi_{jt} + \varepsilon_{it}$$

Where ϕ is the spatial autocorrelation on error, and λ is the spatial autocorrelation coefficient.

The spatial weight matrix is used to determine the proximity of regions to one another because closer regions will have a greater effect than regions that are farther apart (Anselin, 1995). The way to obtain a spatial weighting matrix (W) is to use the information on the distances of the X and Y coordinates from neighbours or the proximity between one region and another based on the Euclidean distance approach (Dattorro, 2015). The spatial weight matrix in this study was calculated using the GeoDa software and the spatial panel data calculation through the STATA software with *spwmatrix* command developed by Jeanty (2014) and *xsmle* by Belotti et al. (2017).

4. RESULTS AND DISCUSSION

In this study, the selection of spatial panel data in the first stage is by conducting the Hausman test to determine the fixed-effect or random-effect model. If the probability value is lower than 0.05, the fixed-effect model is selected and vice versa. Based on the estimation results in Table 1, the Hausman test value (Prob) shows a small number of 0.05, so the best model for SAR and SEM is the fixed effect model. Furthermore, selecting the model between SAR and SEM can compare the Akaike Information Criterion (AIC) value with a minor value criterion and the log-likelihood value with the higher value criterion. Based on Table 1, the best model for Absolute β-convergence analysis is SEM (3), with the smallest AIC value of -7564.81 and the higher log-likelihood value of 3785.4.

Absolute β-convergence indication by the absence of control variables included in the model and only consists of the initial condition variable GRDP per capita on the independent variable. The convergence theory states that the convergence process occurs when the coefficient value of the initial condition variable is negative. Table 1 is in line with the theory, where the initial condition variable (Yt-1) is negative and significant at the 1% level. The coefficient value is −0.1895. From this value, we can calculate the convergence speed and the half-life time using equations (3) and (4). The convergence speed obtained based on SEM (3) is 1.91% per year, with the time required to reach convergence of around 36 years. For comparison of convergence speed other than SEM (3), the following are the results for model (1) is 1.31% per year with a time of about 52 years, model (2) is 0.19% per year with a time of about 349 years, model (4) is 0.25% per year for about 278.56 years. This absolute convergence speed is smaller than the previous study by Vidyattama (2013), which stated that the convergence speed was 3.6% for inter-regencies in Sumatra Island for the 1999-2008 period. Even so, findings of the convergence speed in this study are greater than Aritenang (2014) research results, with a value of 0.6% from 1994 to 2004.

Furthermore, from Table 1, the spatial effect value for the whole model is significant at the 1% level, proving that the included spatial element affects the absolute β-convergence that occurs. In other words, neighbouring areas influence inter-regional convergence on Sumatra Island. Some regencies/municipalities are close to and intersect on one island, resulting in high interaction and interdependence with the surrounding area, especially for meeting primary needs. Besides, urban areas are excellent for people who live in regencies, especially for work activities. The surrounding city area produces an area satellite.

Before we proceed to the conditional β-convergence analysis, the selection of the model is carried out again. The first stage is by conducting the Hausman test to determine the fixed-effect or random-effect model, with criteria that if the probability value is lower than 0.05, then the model selected is the fixed-effect model and vice versa. Based on the results presented in Table 2, the Hausman test value (Prob) shows a value smaller than 0.05, so the best model used in this study is the fixed-effect model listed in the columns: SAR (1) and SEM (3). In the next stage, the AIC and log-likelihood values are compared from the selected models. The best model for conditional β-convergence analysis is SEM (3).

The SEM (3) result states a convergence process as evidenced by the value of the Yt-1 coefficient, which is negative with a value of −0.2281 and is significant at the 1% level. Based on this value, a convergence speed of 2.35% per year is generated with about 29 years to achieve an even distribution of GRDP per capita at steady-state conditions required by several control variables in the model. This convergence speed is greater than the previous study by Aspiansyah and Damayanti (2019) of 1.8% per year and takes about 39 years to cover half the gap.

Based on the results of the SAR model (1) provides evidence that there is a significant spatial effect with a value of 0.3706 and significant at the 1% level. The same thing for the SEM model (3) λ value is 0.4312 and is significant at the 1% level. From the two models, there is evidence that the regional neighbours on Sumatra Island can affect the convergence process. SAR (1) model, spatial effect illustrates that the economic convergence is influenced by the region's characteristics and is also influenced by the convergence of other regions. In contrast, the SEM model (3) illustrates that the convergence of a region is not only influenced by the characteristics of the region itself but also by random shocks that occur from other regions.

Table 1: Absolute β-convergence models for 2010-2020

Item	SAR - FE (1)	SAR - RE (2)	SEM - FE (3)	SEM - RE (4)
Y_{t-1}	−0.1346*** (0.0108)	−0.0216*** (0.0035)	−0.1895*** (0.014)	−0.027*** (0.0041)
Spatial effect				
ρ	0.3196*** (0.0562)	0.4597*** (0.0514)		
λ			0.4948*** (0.0521)	0.4966*** (0.0516)
Convergence speed	1.31	0.1985	1.91	0.2488
Half-life time (year)	52.74	349.16	36.29	278.56
Hausman (Prob)	0.0000		0.0000	
AIC	−7524.447	−7184.5	−7564.814	−7190.47
Log-likelihood	3765.223	3597.25	3785.4	3600.236
R^2	0.0935	0.0825	0.1113	0.1113
N	1694	1694	1694	1694

The spatial model based on Euclidean distance matrix. AIC: Akaike information criterion. Heteroskedasticity robust standard error are shown in parentheses. *P<0.1; **P<0.05; ***P<0.01

Table 2: Conditional β-convergence models for 2010-2020

Item	SAR - FE (1)	SAR - RE (2)	SEM - FE (3)	SEM - RE (4)
Y_{t-1}	−0.2187*** (0.0148)	−0.0231*** (0.0042)	−0.2281*** (0.0153)	−0.02966*** (0.0047)
INV	0.0853*** (0.0189)	0.0079*** (0.0025)	0.0681*** (0.0212)	0.0104*** (0.0026)
BL	0.0146** (0.0064)	−0.0094** (0.0044)	0.0159** (0.0072)	−0.0146*** (0.0052)
Elec	−0.0002** (0.0001)	−0.00001 (0.00006)	−0.0002** (0.0001)	0.00001 (0.00008)
HC	0.00003 (0.0001)	0.00008 (0.00008)	−0.00001 (0.0001)	−0.0001 (0.00008)
Spatial effect				
ρ	0.3706*** (0.0551)	0.4312*** (0.0534)		
λ			0.4071*** (0.0571)	0.4916*** (0.0527)
Convergence speed	2.24	0.2124	2.35	0.2737
Half-life time (year)	30.89	326.24	29.45	253.236
Hausman (Prob)	0.0000		0.0000	
AIC	−7582.711	−7190.739	−7586.23	−7203.34
Log-likelihood	3798.355	3604.369	3800.115	3610.67
R_2	0.1385	0.0411	0.1395	0.0475
n	1694	1694	1694	1694

The spatial model based on Euclidean distance matrix. AIC: Akaike information criterion. Heteroskedasticity robust standard error are shown in parentheses. **P<0.05; ***P<0.01, SAR: Spatial autoregressive

Based on Table 2, there is evidence that investment has a positive and significant effect on convergence with a coefficient value of 0.0681. If there is an increase in investment by one unit, the convergence will increase by 0.0681 per cent, assuming other variables are held constant. These results are in line with research by Balash et al. (2020), Gömleksiz et al. (2017), and Barro (2015), which generally proves that investment has a positive effect on the convergence process. Meanwhile, specifically not for research from Demidova (2021) states that investment in poor and middle-income areas is ineffective.

Furthermore, infrastructure funds affect convergence with a coefficient value of 0.0159 and significant at the 5% level. This result indicates that allocating funds from the centre for regions and regions to manage and allocate infrastructure spending positively supports the convergence process. The results of our study are in line with research by Fageda and Olivieri (2019), Flores-Chamba et al. (2019), Hooper et al. (2018, 2020), and Yang et al. (2016), which proves that infrastructure funds or physical infrastructure are significant to convergence.

From the research results, the energy infrastructure coefficient is negative at -0.0002 and significant at the 5% level, which means that if there is an increase in energy infrastructure by one unit, it will slow down convergence by 0.0002 per cent with the assumption that other variables in the model are considered constant. This energy infrastructure is a proxy of the household electrification ratio, and the highest value of 100 is considered that all households can enjoy electricity. In general, for urban areas and districts, the electrification ratio has reached 98-100 per cent. However, there are still districts with a ratio value below 80 per cent, including Nias, Mentawai Islands, Pelalawan, Indragiri Hilir, and West Lampung districts, that have not fully enjoyed access to electricity, and there are still isolated areas. Electricity infrastructure plays a role in sustainable living. It increases regional productivity to support the convergence process, as proven by Chatterjee (2017) in India. It turns out that for our observation area, it is not proven due to differences in the proxy variables used, and the value of the electrification ratio cannot be more than 100.

Furthermore, the human capital coefficient value is different between the SAR (1) and SEM (3) models, wherein model (1) is positive 0.0003 and model (3) is negative −0.00001, and for both models, there is no significant, so human capital not significant in influencing convergence. The insignificance of human capital puts this result in line with research by Lee (2020), which has previously been proven in middle-income trap countries. Reflecting on the results of previous studies, Sumatra Island is part of Indonesia, and Indonesia is included in the category of middle-income trap countries, so the results make sense. On the other hand, the regional average secondary school participation rate only reached 78.19%, so it is necessary to increase public school participation, especially in the school-age population, and which aims to increase human capital, so in the long-term will have a significant effect on convergence. Meanwhile, these results are not in line with research by Aspiansyah and Damayanti (2019), Lee (2016; 2017), and Lima and Neto (2016), which state that human capital has a significant effect on convergence.

5. CONCLUSION

Based on the above results, the following conclusions can be drawn. First, there is evidence of a convergence process with a speed of 1.91% per year and a half-life time of about 36 years for the absolute β-convergence model, while for the conditional β-convergence, the resulting speed is 2.35% per year with about 29 years. Second, taking into account the spatial element in the model proves that there is an influence from neighbouring areas, which is indicated by the positive and significant spatial effect of the SAR and SEM models. Third, from the results of conditional β-convergence, there is evidence that investment and government spending on infrastructure can support the process of economic convergence between regions. Therefore, the government should maintain an investment climate and develop appropriate and sustainable infrastructure. While electrification is negatively related to convergence, the effect's value is not too large, and the electrification ratio itself will be stuck at the highest value by itself. There will be equality in electricity facilities for households so that policymakers can remain focused on the distribution of electricity facilities, one of the basic infrastructures. The influence of human capital is not significant on convergence. Thus, it is homework for policymakers to increase further school participation, especially in the population of school-age, to increase the existing human capital in their respective regions.

From these results, policymakers can consider the model's significant positive or negative control variables to achieve an even condition of GRDP per capita in steady-state conditions. From a spatial perspective, policymakers should not forget to coordinate between regions in infrastructure development and be sustainable. Suggestions for further research to be able to add variables other than the current model and modify the proxy for energy infrastructure variables.

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