IJEEP
INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY
EJ EconJournals
ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2023, 13(4), 139-149.

EJ EconJournals

The Influence of Investment, Energy Infrastructure, and Human Capital Towards Convergence of Regional Disparities in Sumatra Island, Indonesia; Using Oil and Gas Data and Without Oil and Gas

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Received: 24 January 2023 **Accepted:** 17 May 2023 **DOI:** https://doi.org/10.32479/ijeep.14117

ABSTRACT

This study aims to analyze the level of economic disparity and the influence of several economic and social variables on the convergence process between regions on Sumatra Island by using oil and gas and non-oil data to support the achievement of the 10th goal of sustainable development or SDGs 2030. The dataset used is panel data totaling 154 Regencies/Cities from 2010 to 2020. The analytical tool used is the Theil index, conventional panel data regression approaches, panel spatial data, and comparisons with both approaches to produce the best model. The results of the Theil index show that the disparity trend is decreasing for both data. The disparity value of oil and gas is more remarkable than without oil and gas. Furthermore, comparing the panel data method produces a superior and realistic spatial model. From the spatial model using the SEM approach, the convergence speed for oil and gas is 4.01% with a half-life of about 17 years, and for non-oil and gas, it is 5.37% with a half-life of about 12 years. All variables significantly affect the convergence process and are valid for oil and gas and non-oil and gas data.

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

1. INTRODUCTION

Regional or inter-regional disparities are essential in the economic literature and have attracted the attention of many researchers. Regional disparities left for too long can trigger internal conflicts within a country (Lessmann, 2016) and make something sustainable so that it becomes a civil conflict (Ezcurra, 2019). The international world's attention to this disparity has included it in one of the sustainable development goals or SDGs 2030, which is a state in the 10th goal of "reducing intra- and inter-regional inequality."

The disparity between regions in Indonesia is the main thing because regional disparities that continue to occur can trigger an increase in crime rates, for example, cases in the provinces of Aceh, Riau, East Kalimantan, and Papua (Tadjoeddin et al., 2001; 2020). The provinces of Aceh and Riau locate on Sumatra Island. This island is the second region in Indonesia with rapid development after Java Island, with an average contribution value for Indonesia's Gross Domestic Product (GDP) of 22.23% during the 2010-20 period and Java of 57.85%. Furthermore, for the disparity that occurs with the global indicator of SDGs achievement, namely the Gini coefficient, the Sumatra region is in the moderate category with an average value for the 2010-2020 period, which is 0.34. In addition, there are still underdeveloped areas on the island of Sumatra, around seven regions in 2020, including Nias, Nias Selatan, Nias Utara, Nias Barat, Kep Mentawai, Musi Rawas Utara, Pesisir Barat.

The provincial economy in Sumatra during the last 9 years from 2011 to 2019 raised positively at a fluctuating rate, and for 2020, the entire region experienced a shock caused by the COVID-19 pandemic. The average growth rate in Sumatra from 2011 to 2020 was 4.36%. The province's economic growth rate, with the highest value in 2019, was Sumatra Selatan Province, with a growth rate of 5.71%, and the lowest was Riau Province, at 2.84%; this was due to the declining value of oil lifting. Meanwhile, the income distribution of the Gini ratio in 2011-2020 shows a downward trend from 0.342 to 0.319. In general, there is a disparity between individuals in the moderate category due to the enormous index value of 0.300. The province with the highest average score was Sumatra Selatan at 0.363, and the lowest score was Kep Bangka Belitung Province at 0.287.

Furthermore, this value provides an initial representation of the disparity pattern in which areas with high disparities provide spillover effects to neighboring areas. Based on the neoclassical hypothesis, there was a divergence condition at the beginning of development in developing countries, namely increasing inequality between regions. As development continued, the conditions were convergent (Sjafrizal, 2018), so the existing data indicated a convergence process.

In general, there are two approaches to calculating regional disparities. The first is a static approach, usually using the calculation of the Williamson index and the Theil index. Second, the dynamic approach is based on the Solow economic growth model called sigma and beta convergence. The concept of convergence uses the assumption of diminishing returns to capital, referring to a long-term process in which per capita income in poor areas grows faster than in affluent areas (Barro and Sala-i-Martin, 1992). In this case, catch-up occurs, and eventually, convergence or income per capita between regions will be the same in steady-state conditions (Sala-i-Martin, 1996b).

As time goes by, the development of empirical results from convergence studies states that there is a convergence process, and there are those who say there is a divergence. Recent empirical results from several parts of the world state that there is a convergence process. Including in the European region by Alexa et al. (2019); Balash et al. (2020); Butkus et al. (2018); Demidova (2021); Fageda and Olivieri (2019); Kubis and Schneider (2016); Montresor et al. (2020); Postiglione et al. (2020), in the Americas by Aristizábal and García (2021); Breau and Saillant (2016); Flores-Chamba et al. (2019); Yu and Lee (2012), in the Asia region by Barro (2016); Lee (2016, 2017); Mendez and Santos Marquez (2020); Zhang et al. (2019). On the contrary, some results state that there is divergence, including those by Goschin (2014, 2017); Pietrzykowski (2019); Simionescu (2014) for the European region, for the Asian region by Lolayekar and Mukhopadhyay (2017, 2019), and in Africa by Kant (2019). Meanwhile, specifically, the empirical results in Indonesia which state convergence by Hidayat et al. (2022); Maryaningsih et al. (2014); Mendez (2020); Rahayu et al. (2015); Wau et al. (2016), in contrast to the divergence results by Firdaus et al. (2012). Differences in inconsistent empirical results create gaps for us to fill in and test the convergence process that occurs predominantly in Indonesia.

Convergence spatial research began to develop in the early 2000s and was pioneered by Rey and Montouri (1999) and continues to develop today, starting from serial cross-section data to familiar panel data developed by Elhorst (2014). Furthermore, Capello and Nijkamp (2009) argue that using spatial elements in analyzing economic disparities will be much more realistic than without spatial elements. Research in Indonesia that examines spatial convergence is still tiny. To our knowledge, those conducting studies include Aspiansyah and Damayanti (2019); Hidayat et al. (2022); Vidyattama (2013), and specifically, there is no comparison of conventional and spatial models.

In this article, we have two research objectives. The first is to identify regional disparity trends using GRDP data with oil and gas and without oil and gas. Second, examine the influence of investment, infrastructure funds, energy infrastructure, and human capital on the convergence process that occurs on Sumatra Island at a regional scale to gain a better understanding of spatial convergence and compare conventional panel data models with spatial panel data. The paper is structured as follows: a subsequent section theoretical foundation and a brief review of the research conducted 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 study of development disparities between regions is closely related to the neo-classical hypothesis, starting from the neo-classical regional economic growth theory presented by North (1955). Later became the basis for Borts (1960) to produce a theory of equalizing production factor remuneration. The theory became the basis for explaining why development disparities occur between regions. This neo-classical hypothesis states that: at the beginning of development in developing countries, there will be disparities in development between regions that tend to increase or diverge, but the more advanced the development of a country, the level of disparities between regions will decrease, or a convergence process will occur. Williamson (1965), for the first time, tested the truth of this hypothesis with case studies in developed and developing countries, and his empirical results proved that the hypothesis was correct.

Existing studies on disparities in Indonesia have almost entirely focused on differences at the provincial level, starting from the seminal paper by Esmara (1975) onwards by Akita and Alisjahbana (2002); Hayashi et al. (2014); Kataoka (2010, 2018); Resosudarmo and Vidyattama (2006); Wibisono (2003). Meanwhile, the results of studies on district/municipality units both in Indonesia and from one of the provinces, including by Akita (2003); Firdaus et al. (2012); Hidayat (2014); Hidayat et al. (2018); Mukhlis et al. (2017); Soebagyo et al. (2019). The results of this study state that development disparities occur between regions with fluctuating values in different observation periods.

Based on research in Indonesia, there are differences in the use of methods for measuring the value of development disparities between regions. Including those using the Williamson Index, such as Firdaus et al. (2012); Soebagyo et al. (2019); Wibisono (2003), and the Theil index by Akita (2003); Akita and Alisjahbana (2002); Hayashi et al. (2014); Hidayat (2014); Hidayat et al. (2018); Kataoka (2010); Wibisono (2003). The results of these two indices have their respective advantages; in the Williamson index, the final measurement value is realistic and can explain the position level of development disparities that occur. Meanwhile, the advantages of the Theil Index are that the first is independent of the number of regions, so it can be used to compare disparities from different regional systems. Second, it can be decomposed into disparities between and disparities within groups or groups simultaneously, which then become spatial analysis. Third, it can calculate each region's contribution (in percentage) to the regional development disparities to providing policy implications.

Furthermore, according to Barro and Sala-i-Martin (1991), convergence is divided into two concepts. First, β-convergence is a catch-up process for the economy of poor regions, which is faster than the economy of rich regions, so that in the long run, the level of per capita income between regions will be the same in steady-state conditions. Second, σ-convergence, namely the decline in economic inequality from time to time. According to Sala-i-Martin (1996a), the existence of a necessary condition for σ convergence is the existence of β convergence, and the existence of β convergence will tend to create σ convergence. Nonetheless, the two concepts are not always synonymous. If poor areas grow faster than other more developed regions without seeing a decrease in their dispersion, then convergence β is obtained without obtaining σ convergence. Conversely, suppose a poor area can grow faster so that during the t+T period, the area becomes more prosperous than the other region. In that case, it is said that σ convergence exists without β convergence occurring.

The β-convergence model is further improved by Barro and Sala-i-Martin (1991, 1992) by bringing the idea that poor and rich economies may not converge at the same steady-state conditions. They categorize convergence to the same steady-state condition as absolute convergence and a different steady-state condition as conditional convergence. In conditional convergence, they argue, the expected negative relationship between the initial per capita income level and the growth rate holds only when the structural differences between poor and rich economies are constant. Conditional convergence is characterized by adding other variables apart from the initial conditions.

Research by Balash et al. (2020) and Demidova (2021) prove that investment influences the convergence process that is taking place in Russia. However, investment in poor and middle-income areas is not practical. Meanwhile, poor and medium-sized regions receive a positive spillover from the growth of neighboring regions, which in turn can expect a reduction in the living standards between poor and rich areas. The article by Gömleksiz et al. (2017) found that investment is significant in the convergence process that is taking place in Turkey. Furthermore, Barro (2015) revealed that the investment ratio positively and significantly affects convergence.

Seminal work by Mankiw et al. (1992), or MRW, pioneered the relationship between physical and human capital in economic growth. They state that a combination of physical capital, labor skills, and the accumulation of human capital and physical capital influences the output of an economy. Lima and Neto (2016) research uses the MRW model with spatial expansion, revealing a strong spatial dependence among Brazilian micro-regions. Investment in physical capital and human resources supports the convergence process. Empirical results by Lee (2016, 2017) state that human capital proxied by the average school age and squared has a significant effect. Educational attainment shows that the growth rate increases with educational attainment only when the country has achieved an average of 6.0 years of schooling, which is the threshold level.

Furthermore, Lee (2020) proves that middle-income trap countries that human capital and investment are not significant for convergence. Zhang et al. (2019) found that human capital influences the convergence that occurs in China. Meanwhile, Yang et al. (2016) found that investment in education and health as a proxy for human capital positively affects regional convergence. Furthermore, the empirical results from Aspiansyah and Damayanti (2019) and Hidayat et al. (2022) with a spatial model proving human capital has a significant positive relationship to the convergence process that occurs.

Duranton and Turner (2012) stated that the creation of interstate road infrastructure reduces the disparities between cities in the United States. Similar results by Hooper et al. (2018, 2020) show that investment in infrastructure significantly affects equity between states. Flores-Chamba et al. (2019) emphasized the importance of increasing public spending on productive infrastructure because it significantly influences the convergence process. Crescenzi and Rodríguez-Pose (2012) found that infrastructure is not a significant predictor of economic growth in the European Union, and its impact is far below what is expected from the primary role of infrastructure. The opposite results from Cosci and Mirra (2018) show that the influence of infrastructure is significant but accompanied by an intense polarization between the northern and southern regions of Italy which has failed to be prevented because investment in the south is not significant enough to close the accessibility gap that occurs. Fageda and Olivieri (2019) prove that physical infrastructure positively impacts the convergence process in Spain. Then, Chatterjee (2017) proves that one of the drivers of the convergence process is electricity infrastructure. The results from Mishra and Agarwal (2019) for the Asian region state that energy, transportation, and telecommunications infrastructure significantly reduce the disparities. Results similar to Hidayat et al. (2022) prove that energy infrastructure is significant in reducing inequality. Hadi et al. (2021) found that electricity distribution influences development, especially in the industrial sector.

3. METHODOLOGY

In this study, a quantitative method was used related to the calculation value, which was analyzed from several measuring instruments, including the Theil Index, to measure the level of disparity in regional development. Moreover, conventional and spatial panel data are used as model comparisons to produce the best model. The areas that are the unit of analysis are the 154 districts/municipalities on Sumatra Island. The time series data used is from 2010-2020. The GRDP data used include oil and gas and without oil and gas; this is used to see differences in the results of disparities resulting from oil and gas-producing regions and without oil and gas. Data sources come from several Central Bureau of Statistics surveys, including socio-economic surveys, labor force surveys, population censuses, GRDP with oil and gas and without oil and gas, GRDP per capita, and public finances.

3.1. The Measure of Development Disparity between Regions – Theil Index Method

Calculating the Theil Index (Theil, 1967) helps analyze trends in geographic concentration over a certain period. It can identify a more detailed picture of development disparities between regions by decomposing them into disparities between regions and within regions. The Theil Index equation is written as follows: (Hidayat, 2014)

$$I_T = \sum_{i=1}^{n} y_i \log\left(\frac{y_i}{x_i}\right) \tag{1}$$

Where: I_T is Total disparity (Theil Index), y_i = Provincial GRDP$_i$/Region GRDP, x_i = Provincial Population$_i$/Region Population, $y_i \log(y_i/x_i)$ is partial disparity. The Theil index value is not negative, and a value of 0 reflects perfect equality.

In this study, the Sumatran region was divided into three development areas, namely the northern part or region 1 (Aceh and North Sumatra Provinces), the middle or region 2 (West Sumatra, Riau, Riau Islands, and Jambi Province), and the south or region 3 (Bengkulu, South Sumatra, Bangka Belitung, and Lampung Province). The division of regions is created on growth corridors and the distribution of the Sumatran island area in the 2020-2024 RPJMN document.

Furthermore, to find out the source of development disparities occur, equation (1) is decomposed into between (I_B) and within (I_W) so that the equation becomes as follows:

$$I_T = I_B + I_W \tag{2}$$

$$I_B = \sum_{g=1}^{n} Y_g \log\left(\frac{Y_g}{X_g}\right) \qquad I_W = \sum_{g=1}^{n} Y_g I_g$$

$$Y_g = \sum y_i \qquad X_g = \sum x_i \qquad I_g = \sum_i \frac{y_i}{Y_g} \log\left(\frac{y_i / Y_g}{x_i / X_g}\right)$$

3.2. Conditional Convergence – Panel Data

The absolute β-convergence model can be expanded by adding several control varbles affecting convergence or decreasing economic disparities. Thus, the model is called conditional β-convergence, which is required by several control variables. The control variables in this model are an investment, energy infrastructure, infrastructure, and human capital. The selection of some of these variables is based on the theory previously described and the results of previous studies conducted in various places.

The general equation for the conditional β-convergence model in this study is as follows:

$$\log Y_{i,t} - \log Y_{i,t-1} = \alpha - \beta_1 \log Y_{i,t-1} + \beta_2 \log INV_{i,t-1} + \beta_3 \log Inf_{i,t} + \beta_4 EI_{i,t} + \beta_5 HC_{i,t} + u_{i,t} \tag{3}$$

Description: i is a district/city, t is a time series, and u is an error term.

Convergent conditions occur if the β_1 coefficient is negative; otherwise, a divergent condition occurs if the β_1 coefficient is positive. The coefficient β_1 can be written as follows:

$$\beta_1 = -\left(1 - e^{-\beta T}\right) \tag{4}$$

Where: T is the analysis time. So that the speed of economic convergence between regions to achieve economic equity in steady-state conditions over a particular time can be calculated as follows:

$$\beta = -\frac{\ln\left(\beta_1 + 1\right)}{T} \tag{5}$$

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

$$\tau_{half-life} = \frac{\ln(2)}{\beta} = 0.693147 \cdot \beta^{-1} \tag{6}$$

From equation (3), operationally defined variables include: INV is the investment value subject to a 1-year time lag. This lag assumes that the investment included in the current year will significantly impact the following year to support the achievement in the following year and is a proxy from the value formation of gross fixed capital in units of millions of Rupiah. Meanwhile, Inf is the value of infrastructure proxied from infrastructure spending. The EI variable or energy infrastructure is proxied from the household electrification ratio, indicating household access to electricity. Finally, HC, or human capital, which is an investment in human capital from an educational perspective, is a proxy for the Net Enrollment Rate (NER) at the high school level. The NER shows how much of the population attends school on time to the school-age group at the level of education taken.

Panel data is a combination of cross-section and time series. To take into account the individuality of each cross-section unit, this can be done by making the intercept different in each region, so in the fixed effect model (FEM), a dummy variable is added to change the intercept, but the other coefficients remain the same. So the model equation is written as follows:

$$Y_{it} = \alpha + \beta_j X_{it} + \sum_{i=1}^{i} D_i^c \alpha_i + \mu_{it} \tag{7}$$

As for the random effect model (REM), there is a fundamental difference from FEM, in which the specific effect of each α_i is used as part of the random error component and has no correlation with the observed explanatory variable (X_{it}). Thus the REM equation is written as follows:

$$Y_{it} = \alpha_i + \beta_j X_{it} + E_{it} \quad (8)$$

$$E_{it} = (\mu_{it} + v_t + w_{it})$$

Description: $\mu_i \sim N(0, \delta_u^2)$ component cross-section error, $v_i \sim N(0, \delta_v^2)$ component time-series error, $w_{it} \sim N(0, \delta_w^2)$ component error combination.

The formulation of the random effect model is obtained from the fixed effect model by assuming that the average effect of random time series and cross-section variables is included in the intercept and that the random deviation from the mean is equal to the error component, μ_i and v_t. The appropriate method for estimating the random effects model is Generalized Least Squares (GLS), assuming there is no homoscedastic correlation and no cross-sectional correlation.

Panel data spatial regression models with specific interactions between spatial units will have a dependent variable of spatial lag or spatial processes on errors usually referred to as spatial lag models and spatial error models (Elhorst, 2014). The spatial lag model states that the dependent variable depends on the neighboring dependent variables and local characteristics. The following is a spatial lag or Spatial Autoregressive (SAR) model.

$$y_{it} = \rho \sum_{j=1}^{N} W_{ij} y_{jt} + x_{it}\beta + \mu_i + \varepsilon_{it} \quad (9)$$

where ρ is the spatial autoregressive coefficient, and W_{ij} is the spatial weighting matrix element (W).

Furthermore, the spatial error model (SEM) states that local characteristics and correlated errors between spaces spatially influence the dependent variable. The following is the spatial error model equation (SEM).

$$y_{it} = X_{it}\beta + \mu_i + \phi_{it} \quad (10)$$

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

Where ϕ is the spatial autocorrelation of errors, and λ is the coefficient spatial autocorrelation.

In the SAR and SEM models in panel data, there are fixed effect and random effect approaches, so to choose the approach to be used Hausman test is carried out, which is also found in conventional panel data. With the criteria, if the probability value is <0.05, the model chosen is the fixed effect model and vice versa.

The spatial weight matrix is used to determine the proximity of regions to one another because closer areas will have a more significant effect than areas that are farther away (Anselin, 1995). The way to obtain the spatial weighting matrix (W) is by using the information on the distance of the X and Y coordinate points from neighbors 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 GeoDa software and spatial panel data calculations through STATA software with the *spwmatrix* command developed by Jeanty (2014) and *xsmle* by Belotti et al. (2017).

4. RESULTS AND DISCUSSION

4.1. Analysis of Development Disparities between Regions

The results of the Theil Index using oil and gas and non-oil and gas GRDP for 2010-2020 are presented in Figure 1. The oil and gas Theil Index values have fluctuated and tended to decrease from 2010 to 2020 with a value of 0.113-0.072, and these results indicate that there is economic disparity between regions in Sumatra. Furthermore, there has been an increase in the 2020 disparity value due to a decrease in each province's GRDP value. The COVID-19 pandemic has resulted in a contraction in the GRDP sector. In addition, the increasing turmoil was caused by an increase in the population of several provinces on Sumatra Island. The same trend results were obtained for the Theil index without oil and gas, namely a decrease in value from 0.069 in 2010 to 0.052 in 2019; the decline in the index value without oil and gas is more stable than the oil and gas index value.

Next, the more significant disparity in oil and gas than without oil and gas can be seen every year. The most significant difference occurred in 2010, where the oil and gas index value was 0.113, and in non-oil and gas, it was 0.069, and in 2019 the distance between the two narrowed with a difference of 0.013, from 0.065 value oil and gas and 0.052 without oil and gas. The difference in oil and gas Theil index values and without oil and gas indicates that oil and gas natural resources play a role in causing disparities between regions. The activities of the oil and gas industry generally use a relatively high level of technology, so the absorption of local workers, who are primarily low-skilled, is minimal. On the other hand, the link between oil and gas activities and local economic activities is also tiny, and most of the revenue derived from these activities flows out of the region. The implication is that the positive impact of oil and gas production activities on the local economy is not as significant as expected.

Based on the trend of decreasing disparities, it illustrates that the disparities that occur are in the process of convergence based on the neo-classical hypothesis concept, which states that the more advanced the development of a region, the process of reducing the level of disparities will occur. This downward trend is consistent with previous research on disparities, including by Akita (2003) and Kataoka (2010, 2018), which occurred in the post-crisis period up to 2010.

The economic disparity between regions in Sumatra comes from within and between development areas, as shown in Figure 2. Sources of economic disparities between regions in Sumatra in the 2010-2020 period using oil and gas data originate from within the development area with an increasing trend from 53.8% to 56.3%, while the disparity originating between development areas decreased from 46.2% to 43.7%. Meanwhile, results from non-oil and gas data for sources of disparity also come from

Figure 1: Development disparity trends between regions, 2010-2020

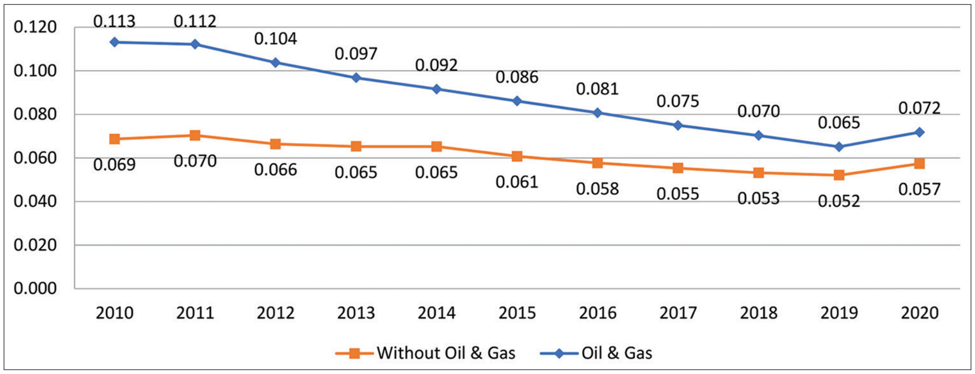
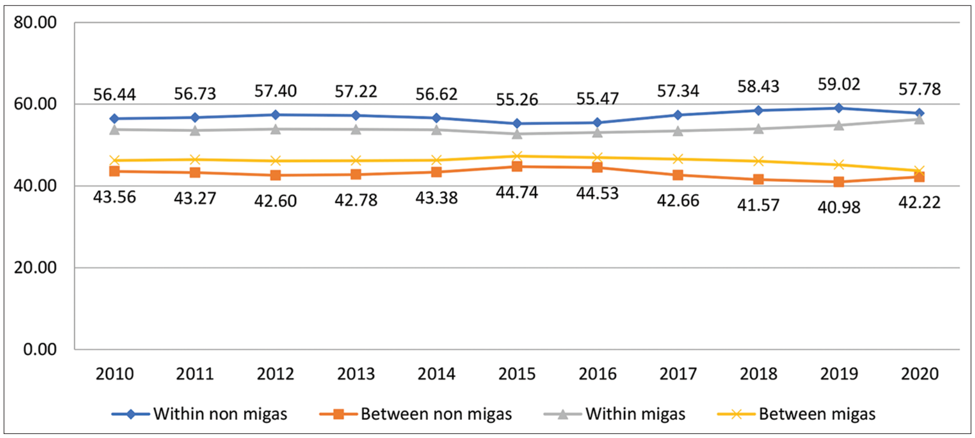


Figure 2: Sources of development disparities between regions (%), 2010-2020



within development areas, with an increasing trend from 56.4% to 57.8%. There is a non-significant decrease in disparities between development areas from 43.6% to 42.2%.

Based on these results, it is clear that the regions within the development area are the triggers for disparities. In other words, the neighboring factors in one area affect the economic disparities. Each development region consists of several provinces directly in contact with regional administrative boundaries and the distance between provincial capitals. From this, it can be stated that neighboring regions' economic conditions affect neighboring regions or are interdependent. Region 2, consisting of the Provinces of Riau, Kep Riau, West Sumatra, and Jambi, have different economic characteristics. However, they are interdependent, as is the case for agricultural commodities, primarily sourced from West Sumatra Province for this region. However, the enormous contribution of the oil and gas sector played a vital role in producing a large per capita GRDP for the Provinces of Riau, Riau Islands, and Jambi.

Furthermore, the decomposition value of Theil Index states that during the 2010-2020 period, economic disparities between regions were influenced from within the development area (Region 2), which in this region contained Riau Province and Riau Kep with an enormous contribution value to development disparities in Sumatra. This is due to the area's considerable per capita GRDP value, calculated by oil and gas and non-oil and gas, in 2020, including oil and gas for Riau Province amounting to 76.88 million Rupiah and Riau Island Province amounting to 85.01 million Rupiah. While for data without oil and gas, the PDRB per capita for Riau Province is 66.14 million Rupiah, and for Riau Island Province is 68.33 million Rupiah. In addition, Riau Province and Riau Islands are dominant oil and gas producers. In particular, Riau Islands Province is a region directly adjacent to Singapore, so the trade and tourism sector is excellent. The existence of Riau Province and Riau Islands as the most significant contributors is in line with research from Akita and Alisjahbana (2002), and Akita (2003) stated that Riau Province was one of the areas causing disparities in the 1993-97 period.

4.2. Conditional β-convergence Analysis

In this study, convergence was proved using two approaches: conventional panel data and spatial panel data. The initial procedure for selecting the panel data model is by carrying out the Hausman test to determine FEM or REM, with the criterion that if the probability value is <0.05, then the model chosen is FEM 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 both approaches is FEM. Furthermore, specifically for the spatial approach, a model selection is made between SAR and SEM by comparing the Akaike Information Criterion (AIC) value with the smallest value criterion and the log-likelihood value with the largest value criterion. Based on Table 1, the best model for the β-convergence spatial approach on the oil and gas side is the SEM model (3), with the smallest AIC value of −8898.57 and the largest log-likelihood value of 4456.28. The best model

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

Item	Oil and Gas			Without Oil and Gas		
	FEM	SAR–FE	SEM–FE	FEM	SAR–FE	SEM–FE
	(1)	(2)	(3)	(4)	(5)	(6)
Y_{t-1}	−0.3281***	−0.3086***	−0.3565***	−0.3994***	−0.3818***	−0.4459***
	(0.0681)	(0.0132)	(0.0141)	(0.0783)	(0.0152)	(0.0167)
INV_{t-1}	0.0827**	0.1019***	0.0653***	0.1547***	0.1703***	0.1182***
	(0.0365)	(0.0119)	(0.0150)	(0.0463)	(0.0134)	(0.0185)
Elec	−0.00008	−0.00007	−0.0001***	−0.0001	−0.0001*	−0.0002***
	(0.0001)	(0.00006)	(0.00006)	(0.0001)	(0.00006)	(0.00007)
Inf	0.0196**	0.0166***	0.0226***	0.0183**	0.0154***	0.0199***
	(0.0083)	(0.0044)	(0.0051)	(0.0078)	(0.0044)	(0.0053)
HC	0.0003***	0.0003***	−0.0002***	0.0003***	0.0002***	0.0002**
	(0.0001)	(0.00007)	(0.00008)	(0.0001)	(0.00007)	(0.00008)
Spatial effect						
P	-	0.4479***	-	-	0.3861***	-
		(0.0445)			(0.0468)	
Λ	-	-	0.6318***	-	-	0.6994***
			(0.0435)			(0.0496)
Convergence speed	3.61	3.35	4.01	4.63	4.37	5.37
Half-life time (year)	19.17	20.66	17.30	14.96	15.85	12.91
Hausman (Prob)	0.000	0.000	0.000	0.000	0.000	0.042
AIC	−8738.46	−8823.46	−8898.57	−8712.67	−8770.36	−8864.45
Log-likelihood	4374.23	4418.73	4456.28	4361.33	4392.18	4439.22
R^2	0.2831	0.2488	0.2710	0.3078	0.2786	0.2708
N	1694	1694	1694	1694	1694	1694

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

for the non-oil and gas side is SEM (6), with the smallest AIC of −8864.45 and the largest log-likelihood of 4439.22.

Before we proceed to the analysis of conditional β-convergence, the selection of a model between conventional and spatial is made by comparing the smallest AIC value and the largest log-likelihood. As previously known, for conventional obtained, the FEM model (1) (4), and spatial obtained, the best model is SEM (3) (6). Based on the AIC comparison value, the smallest and largest log-likelihood values are obtained in the SEM (3) model for the oil and gas side. SEM (6) for the non-oil and gas side, so the best model for conditional β-convergence analysis is spatial panel data.

SEM (3) results for data including oil and gas state that convergence is evident from the Y_{t-1} coefficient value, which is negative at −0.3565 and is significant at the 1% level. Based on these values, a convergence speed of 4.01%/year is obtained with about 17 years to achieve the equity required by control variables in the model. Meanwhile, the results from the non-oil and gas side of SEM (6) obtained a negative Y_{t-1} coefficient of −0.4459 and significant at the 1% level, so the results of the convergence speed obtained were faster than those including oil and gas, which was 5.37%/year with a half-life time of 12 years.

This achievement without oil and gas was because the economies of regions that are not oil and gas producers are more stable than those of oil and gas producing regions which are highly dependent on the lifting of the oil they produce and fluctuations in world oil prices. Suppose we relate this result to the value of the previous disparity finding, which said that the value of the disparity on the oil and gas side is greater than that on the side without oil and gas. In that case, equity will be faster on the side without oil and gas than on the oil and gas side. Therefore, it is appropriate for the economy in oil and gas-producing regions to develop their potential apart from oil and gas mining so that the economy's dependence on the oil and gas mining sector begins to decrease. Furthermore, this convergence speed is greater than previous research by Aspiansyah and Damayanti (2019) of 1.8%/year. It takes around 39 years to cover half the gap, and Hidayat et al. (2022) of 2.35% with a half-life of around 29 years.

The results of the SAR (2) model of oil and gas and SAR (5) without oil and gas provide evidence of a significant spatial effect with P values of 0.4479 and 0.3861 and are significant at the 1% level. The same is true for the SEM (3) oil and gas and SEM (6) models without oil and gas with λ values of 0.6318 and 0.6994, which are significant at the 1% level. From the two models, there is evidence that neighboring areas on Sumatra Island can influence the convergence process that occurs. As for the SAR model, the spatial effect illustrates that the region's characteristics influence a region's economic convergence, which also influences the convergence of other regions. In contrast, the SEM model (3) illustrates that a region's convergence is influenced by the region's characteristics and a random shock from other regions.

The comparison of the models above provides a new understanding that the use of panel data spatial models is more realistic than conventional panel data models. In other words, including spatial elements in the convergence analysis will be much more realistic than without spatial elements. There are differences in the results of the convergence speed and significant variables in the model. For the speed of convergence, from the oil and gas side, the difference in convergence speed states that the spatial model is 0.4% faster/year and has a half-life time of about 2 years. While for the non-oil and gas side, the spatial model is superior at around 1%/year and a half-life of about 2 years. Meanwhile, from the significance of the control variables, the spatial model for both sides states that all control variables are significant. In contrast, for the conventional model, there is one that is not significant, namely energy infrastructure.

Furthermore, the discussion of control variables uses a superior SEM spatial model. Based on Table 1 from the oil and gas side, the Investment coefficient value (INV_{t-1}) is 0.0653, and significant at the 1% level, this means that if there is an increase in investment in the previous year by one percent, it will accelerate economic convergence between regions by 0.0653, assuming cateris-paribus and having a significant influence. Meanwhile, from the non-oil and gas side, the investment coefficient value is 0.1182 and is significant at the 1% level. The coefficient value is greater than the oil and gas data. This difference in value indicates that investments in non-oil and gas producing regions are more supportive of the economy because these areas are not dependent on lifting and the oil and gas industry. In contrast, oil and gas producing areas are highly dependent on lifting achievements and the oil and gas industry and investment relative to the oil and gas industry.

This finding strengthens the initial hypothesis that investment is one of the driving factors for convergence. In addition, these findings align with the Solow growth model, which emphasizes the role of investment in accumulating physical capital. These findings prove that investment activity in the past year has affected today's economy. The significance of this investment is in line with several previous studies, including Balash et al. (2020) and Demidova (2021), which find that investment influenced convergence in Russia in the 2010-14 and 2000-17 periods. Following on from the findings of Gömleksiz et al. (2017) and Barro (2015) found that investment significantly affects convergence. Then the empirical results in Indonesia by Hidayat et al. (2022) stated that investment is significant for convergence.

From the research results, the energy infrastructure coefficient from the oil and gas side is −0.0001 and significant at the 1% level, which means that if there is an increase in energy infrastructure by one unit, it will slow down convergence by 0.0001% assuming cateris-paribus. While from the side without oil and gas, the coefficient value is −0.0002 and is significant at the 5% level, and the coefficient value is greater for oil and gas data. Based on the difference in the value of this coefficient, it indicates the similarity that occurred in the original, that in real terms, oil and gas-producing areas have adequate electricity infrastructure than non-oil and gas-producing regions, this is due to the operating oil and gas industry, so the impact spreads to households as electricity users. Energy infrastructure is the proxy for the household electrification ratio, and the highest value is 100, which means that all households can enjoy electricity. The electrification ratio has generally reached 98-100% for urban areas. However, there are still districts with ratios below 80%, including Nias, Mentawai Islands, Pelalawan, Indragiri Hilir, and West Lampung, so it can be said that these areas have not enjoyed complete access to electricity. Electricity infrastructure plays a role in a sustainable life. It increases regional productivity to support the convergence process, which has been proven by Chatterjee (2017) in India. It turns out that for our observation area, it is not proven due to differences in the variable proxies used and electrification ratio values that it is impossible to have more than 100. The results align with this study from Hidayat et al. (2022).

Next, the Infrastructure variable has a significant positive impact on the convergence between regions, as evidenced by the coefficient being positive for oil and gas yields of 0.0226 and non-oil and gas yields of 0.0199 and is significant at the same level of 1%. This finding states that infrastructure is one of the factors influencing the growth of per capita income, thereby driving the economic convergence between regions on Sumatra Island. At the same time supports the initial hypothesis that infrastructure is one of the factors driving the acceleration of convergence. Infrastructure is one of the essential fundamental aspects of sustainable development, especially if there is a fulfillment of basic infrastructure such as roads, electricity, and water. Based on the results, it is appropriate for infrastructure to be fulfilled and improved in terms of quality and quantity, especially for interconnections between regions. So the mobility of goods and people becomes smooth because these spatial results state that positive inter-regional linkages positively impact neighboring regions' development.

The findings align with research from Cosci and Mirra (2018); Fageda and Olivieri (2019) state that infrastructure significantly affects convergence, thus emphasizing that the availability of basic infrastructure is an important condition for achieving sustainable growth. Next, the findings by Hidayat et al. (2018) and Hooper et al. (2018) stated that infrastructure significantly affects economic equity between regions. Meanwhile, the findings from Flores-Chamba et al. (2019) emphasized the importance of increasing public spending on productive infrastructure to support the convergence process.

The last control variable is Human Capital, which has a positive and significant influence on the convergence process statistically at the level of 1% and 5%. The coefficient value obtained is the same on the oil and gas and non-oil and gas sides, equaling 0.0002, which means that an increase in human capital can increase growth income per capita of 0.0002 which will always accelerate convergence with the assumption of ceteris paribus. These findings reinforce the initial hypothesis that human capital is one of the factors that influence convergence between regions in Sumatra. Human capital in this study is proxied from the educational dimension with the indicator used, namely the Net Enrollment Rate (NER) at the High School/equivalent level. In real terms, the net enrollment rate (NER) in districts and cities ranges from 41% to 87% in 2020; the development of NER from 2010 to 2020 has fluctuated with an increasing trend. NER describes the participation and access of the population to school at a certain level according to the age group at that level or, in other words, the population who attends school on time. Besides that, a high NER indicates more excellent opportunities for access to education in general. According to Schultz (1961), an increase in investment in human capital through education and training will improve the way of production, improving the economy.

These results align with previous empirical results by Lima and Neto (2016), where human capital is significant in supporting the convergence process. Furthermore, Lee's (2016, 2017) findings state that human capital as a proxy for the average length of schooling significantly affects convergence. Then, the findings from Aspiansyah and Damayanti (2019) and Hidayat et al. (2022) stated that human capital significantly affects convergence between provinces in Indonesia. Meanwhile, these findings do not align with Lee's (2020) finding that human capital is not significant for convergence in middle-income trap countries.

Based on the results of the best model, namely SEM, when linked to the 10^{th} SDG's 2030, namely reducing intra- and inter-regional inequality, the results of this study provide an overview of the achievement of reducing economic disparities between regions in Sumatra Island based on the speed of convergence. The result is the next 12 years, estimated in 2032. The difference in these 2 years makes it an extra task for policymakers to take strategic policies in controlling variables that significantly impact accelerating convergence to achieve the 10^{th} goal of SDG. Of the three variables, the investment variable has an enormous coefficient value of the two variables. Therefore, significant and sustainable investments are still needed in each region.

5. CONCLUSION

Based on the results and discussion above, it can be concluded that some of these will be categorized based on the analytical tools used. First, it is proven that there are still disparities between regions in Sumatra as measured by the Theil Index, with the resulting trend decreasing using both oil and gas data and without oil and gas. This declining pattern indicates a convergent state based on the neo-classical hypothesis. Furthermore, the decomposition of the oil and gas Theil Index states that the source of disparities comes from within development areas, with an increasing trend from 53.8% to 56.3%. Meanwhile, the Theil Index without oil and gas states that the source of development disparity comes from within development areas, with a slowly increasing trend from 56.4% to 57.8%. Thus, it can be stated that the area within the development area triggers disparities between regions. Second, comparing models produces a spatial model that is superior and more realistic than conventional models. Besides that, considering the spatial elements in the model proves that there is influence from neighboring areas marked by the spatial value of the positive and significant effects of the SAR and SEM models. It tests the conditional β-convergence by adding a control variable to the model, accelerating the convergence process. The results for oil and gas data from the fixed effect model obtained a convergence speed of 3.61%/year with a time needed for equalization of around 19 years, and for the spatial SEM model, a speed of 4.01%/year and the time to achieve equalization of around 17 years. The result of using non-oil and gas data is that the convergence speed of the fixed effect model is 4.63%/year, and the time for equalization is around 14 years. From the SEM spatial model, it is obtained that the speed is 5.37%/year, and the time needed for equalization is around 12 years. From the SEM oil and gas and non-oil and gas spatial models, it is found that investment, infrastructure, and human capital have a positive and significant effect on accelerating convergence between regions on the island of Sumatra.

From these results, policymakers can consider that to achieve equal distribution of GRDP per capita in steady-state conditions by considering the significant control variables contained in the model. From a spatial perspective, policymakers must continue coordinating between regions in sustainable infrastructure development. In addition, to support the achievement of the 10^{th} goal of SDG 2030, the government must provide treatment to significant variables, especially in investment, by providing push-ups twice as much as the previous value, and still with an element of equity for each region.

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