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REGIONAL GROWTH, CONVERGENCE, AND HETEROGENEITY IN SUMATERA: EVIDENCE FROM NEW SATELLITE DATA

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ABSTRACT

The use of night-time lights data is increasingly applied for assessing performance of economies. This paper attempts to examine regional growth convergence across 147 districts in Sumatera over the period 2012-2020 using satellite night-time lights data. We firstly evaluate the usefulness of the night-time lights indicator in the context of Sumatera regions. Results show that almost 77 percent of the variability in (official) GDP per capita can be explained by this night-time lights data of GDP. Next, given its potential advantage for predicting regional GDP, we evaluate the existence of convergence and the role of spatial heterogeneity across Sumatera districts. Our findings support the evidence of heterogeneity both in convergence patterns and the role of growth determinants across districts, in addition to observed overall (average) process of regional convergence. Specifically, the northern parts of Sumatera experience a higher speed of convergence compared to the southern area. In addition, internet and credit access demonstrate significant yet different magnitude across Sumatera districts. Looking from policy perspectives, our findings suggest that *one-size-fits-all* policy is not desirable for promoting equal growth across Sumatera districts. Spatial-based policies are instead more demanded to support equal growth.

Keywords: convergence, satellite night-time lights, GWR, Sumatera

1. Introduction

Indonesia is the world's largest archipelagic country with its resource endowments, population density, location of economic activity, ethnicity, and ecology. The disparity in regional development status and environmental conditions has long been a crucial issue in this country (Hill et al., 2008; B. P. Resosudarmo & Vidyattama, 2006; B. Resosudarmo & Vidyattama, 2007). It is also acknowledged that Indonesia has abundant natural resources such as oil, gas and minerals as well as rich marine resources and forestry.

However, these resources are not equally allocated across regions in the country. Oil and gas are found mostly in Sumatera, such as Aceh, Riau, South Sumatera and a part of Kalimantan (East Kalimantan). Mineral ores are abundant in Papua, tin on the island of Bangka, nickel in South Sulawesi and North Maluku, and coal in most of Kalimantan and West Sumatera. Forests are mostly located in Sumatera, Kalimantan, and Sulawesi, while marine resources are mostly concentrated in the eastern Indonesia.

Table 1. GDP Share to National GDP by Island, 2015-2019

Island	GDP growth (%)				
	2015	2016	2017	2018	2019
Sumatera	22.21	22.03	21.66	21.58	21.32
Java	58.29	58.49	58.49	58.48	59
Kalimantan	8.15	7.85	8.2	8.2	8.05
Sulawesi	5.92	6.04	6.11	6.22	6.33
Bali and Nusa Tenggara	3.06	3.13	3.11	3.05	3.06
Maluku and Papua	2.37	2.46	2.43	2.47	2.24
Total (%)	**100**	**100**	**100**	**100**	**100**

Source: Central Bureau of Statistics

Sumatera is the second most populous island in Indonesia after Java (BPS-Statistics Indonesia). From the economic standpoint of view, Sumatera also has contributed the second largest of GDP as the growth engine in Indonesia economy after Java (59 percent) as much

21.32 percent of total national GDP in 2019. Meanwhile, some eastern islands are still left behind.

Although Sumatera has great potencies to develop due to its heterogeneity and resources, the growth performance across and within provinces still face inequalities. Some districts (provinces) are growing faster yet some others can not catch-up the left-behind. It is against SDG's Goals 10 which is to reduce inequality within and among countries. In some extent, spatial effect plays a vital role in the development process of a country, especially Indonesia, which has unique and insular geography. Spatial heterogeneity will lead regions to implement different treatment and policies for the sake of catching-up process towards equality.

Given this research landscape, we draw non-spatial and spatial convergence framework model to address four related questions: (i) Is there regional growth convergence across Sumatera districts? and (ii) To what extent do spatial heterogeneity play a role in the convergence process? (iii) What are the key factors to boost the growth convergence in Sumatera? (iv) Are there different magnitude of those factors in affecting the regional growth of each region in Sumatera? To answer these questions, this paper applied a new spatial econometric model namely, Geographically Weighted Regression (GWR) that can cover the shortcoming of OLS model, by capturing spatial heterogeneity.

The main findings of present paper aim to contribute to the literature on regional growth and convergence in Sumatera in four fronts. *First,* the satellite data can be used to capture the economic activities and explain the variability of GDP growth across Sumatera districts. *Second*, regional growth convergence is present in Sumatera over the period 2012-2020. *Third*, convergence speed across districts in Sumatera demonstrate the heterogeneous pattern. Overall, the northern parts of Sumatera provide a higher speed of regional growth convergence compared to the southern area. Specifically, districts in North Sumatera, West

Sumatera, Bengkulu, and Lampung provinces exhibit obvious convergence to higher income levels. *Fourth*, the positive effect of credit access and internet (digitalization) to growth is significantly inevitable in Sumatera districts, except in Aceh Province and a few settled outer islands in Sumatera Utara and Kepulauan Riau.

The rest of this paper is organized as follows. Section 2 provides the related literature on regional convergence across countries and Indonesia and its application on night-light data. Section 3 describes the methods, data, and stylized facts. Section 4 presents the results and discussion and Section 5 offers some policy implications and concluding remarks.

2. Literature review

Triggered by the seminal paper of (Barro, 1991), numerous studies have been implemented to evaluate income convergence. The focus of those studies not only to undertake convergence analyses across countries at the global level, but also to seek for convergence evidence at the regional and within-country level. In general, the root of convergence studies is the standard proposition of the neoclassical growth model; in the long-run, economies would move to a common steady state given the condition of common preferences and technologies across economies (Barro & Xavier Sala-i-Martin, 1992; Islam, 2003; Mankiw et al., 1992).

In the convergence literature, there are two main methodological frameworks to estimate convergence. First, the classical analysis of sigma (σ) and beta (β) convergence. While the main analysis of sigma convergence is on the decreasing or increasing income dispersion over time, beta convergence tests if lower income economies grow at the higher rates than higher income economies during a given period. Under diminishing returns to capital assumption in the neoclassical growth theory, marginal returns to capital would be greater in an economy with a less stocks of capital than an economy with more capital stocks.

This condition eventually would generate higher economic growth rate in economies with less capital accumulation (Solow, 1956). In other words, investment in capital stocks gives higher yield and thus more lucrative in less developed economies. This better position helps poorer economies to catch up the more developed economies over time. In economic literature, this type of catching up process refers to absolute or unconditional beta convergence. In the condition where absolute convergence exist, there is tendency that income disparity across economies to shrink (Xavier X. Sala-i-Martin, 1996), referred to as sigma convergence.[1] Second, convergence framework that emphasizes the heterogeneous behavior and multiple equilibria. The application of this convergence framework can be divided into two main groups; distribution dynamics (Quah, 1997) and club convergence (Phillips & Sul, 2007, 2009).

The present study is focused on analyzing beta convergence within island in a country. Exploiting region level (within a country) data to study income convergence is particularly advantageous because the sample are relatively homogenous and at the same time, there is freer mobility in capital, labor, and technology (Higgins et al., 2006). Realizing these benefits, within-country convergence studies have been implemented in many developing and developed countries, including in Indonesia, China, India, Slovenia, Colombia, Brazil, Russia, Canada, Japan, and the USA (Aginta et al., 2020; Azzoni, 2001; Banerjee & Jesenko, 2015; Barro et al., 1991; Cherodian & Thirlwall, 2015; DeJuan & Tomljanovich, 2005; Guriev & Vakulenko, 2015; Kakamu & Fukushige, 2005; B. P. Resosudarmo & Vidyattama, 2006; Royuela & García, 2015; Weeks & Yudong Yao, 2003; Xavier X. Sala-i-Martin, 1996). Interestingly, in general the findings of intra-country analyses are not so different to the

[1] However, as pointed out by Sala-I-Martin (1996a), β-convergence is necessary but not sufficient for σ-convergence.

results of many cross-country studies; there is persistent different growth trajectories across regions within countries.

These empirical evidence of lack of sigma convergence within countries are possibly due to the amplification in the magnitude of shocks in the country and thus resulting in larger variance in regional balanced growth paths over time (Young et al., 2008). This violates the hypothesis of the simple versions of beta and sigma convergence models that assumes the absence of externalities and increasing returns to capital. In the later development of convergence literature, (Mankiw et al., 1992) introduce more realistic assumptions that allow for heterogeneity in human capital, savings rates, other preferences and technologies that can influence the equilibrium of the steady state growth. These assumptions rise the possibility for reaching different steady states among economies. Under these conditions, this model predicts there will be inverse relationship between the growth rate of the economy and the distance of the economy from its specific steady state determined by the underlying state variables (Xavier X. Sala-i-Martin, 1996).

2.1. Convergence studies in Indonesia

In this paper, we evaluate convergence across district in Sumatera region of Indonesia, the largest economy in South East Asia that consists of hundreds of ethnic groups with many different cultures and religious beliefs. The multidimensional diversity across regions makes Indonesia as one of countries that is attractive for applying regional and spatial analyses. Numerous scholars have implemented various convergence frameworks analyses to study regional convergence at regional level in Indonesia. Employing beta convergence analysis, Garcia & Soelistianingsih (1998) evaluate convergence in income per capita across provinces in Indonesian in 1975–1993 period. Their findings show the evidence of convergence in regional income and imply that income differences can be reduced by half after thirty to forty years. However, as argued by Hill et al. (2008), the evidence of convergence shown in the study of Garcia & Soelistianingsih (1998) might be only observed in period of analysis and biased due to the influence of oil and gas industries in some regions. To support their arguments, Hill et al. (2008) show the insignificant regional income convergence during 1997-2002 period, remarked by the catastrophic Asian Financial Crisis (AFC) and its aftermath. These findings are also supported by Tirtosuharto (2013). Applying classical sigma and beta convergence, he shows the absence of regional income convergence not only during the AFC and in the period of economic recovery, but also in the earlier years of the decentralization era.

Regional convergence studies using district level data suggest similar evidence. The study of Akita, (2002) shows that income dispersion tends to increase during 1993–1997. Interestingly, the study also captures that the widening income disparity is experienced by districts within some provinces. Similarly, Akita et al. (2011) show the expanding regional income inequality across Indonesian districts after the AFC until 2004 and remained unclear afterwards. Using similar approach, Vidyattama (2013) provides ambiguous results on convergence. Although the beta estimates suggest convergence during 1999–2008 at both the district and the provincial levels, the Williamson index increases slightly, yet insignificant. Nevertheless, throughout the study, he shows that in general the trend of convergence is still very unstable.

2.2. The use of satellite data

Recently many researches and economists use satellite night-time light data to study economic phenomena, particularly in locations where official statics are unavailable or non-comparable (Lessmann & Seidel, 2017; Mveyange, 2018; Nordhaus & Chen, 2015). The justification of using satellite night-time lights data to evaluate economic performance has been shown in numerous studies. Among others, the study by Henderson et al. (2012) concludes that economic growth has strong and significant relationship with changes in night-time lights intensities. The explanation behind these findings is intuitive. In general, most economic activities in night produce or need lights. If the luminosity intensity at night-time lights in a particular location is high, one can assume that the level of economic activities in that location is also high. With respect to income, the more money people have, the more likely they are to have lights on at night. Businesses will also stay open later, resulting in even more light.

The advantage of satellite night-time lights data to study at economic performance at the sub-national level has been also emphasized (Chen & Nordhaus, 2011; Henderson et al., 2012). For that reason, many studies have been exploiting satellite night-time lights data to reveal and discover new patterns. Probably the study of Lessmann & Seidel (2017) is one of the most extensive studies that utilizes satellite night-time lights data to evaluate income disparities at sub-national regions around the world. They start their analyses by predicting per capita GDP at sub-national level in 180 countries over the 1992–2012 period. They continue by using GDP measurement based on luminosity to show that within-country sigma convergence has been observed in approximately between 67 to 70% of all countries world-wide. Finally, they conclude that the difference in natural resources endowment, degree of trade openness, transportation costs, aid, federalism and human capital are the significant determinants of regional inequality. A group of other studies have been also implemented to evaluate convergence within specific region or country. The study by Henderson et al. (2012) finds difference behavior between coastal versus non-coastal areas in sub-Saharan Africa, where the coastal areas do not necessarily grow at a faster speed than non-coastal areas. Still in Africa, Mveyange (2018) finds that regional income inequality in the region increases between 1992 and 2003 but decreases between 2004 and 2012. In Asia, Mendez-Guerra & Santos-Marquez (2020) show that night-time lights luminosity can explain around 60% of the distribution in official GDP per capita data across 274 sub-national regions of the Association of South East Asian Nations (ASEAN) over the 1998–2012 period. Their results on convergence analysis using per capita GDP based on luminosity indicate there is persistent regional inequality within most countries in ASEAN in spite of the presence of regional convergence process. At a country level, Carrington & Jiménez-Ayora (2021) use satellite data from the National Oceanic and Atmospheric Administration to proxy income and analyze economic convergence between provinces and cantons in Ecuador during 1992–2013 period. Their findings of convergence across Ecuador's provinces imply convergence speed at 2% per annum, with the major progress in economic convergence was made over the 1992–2002 period, where the political and economic instability in the country was at the unfavorable levels.

3. Methods, data and stylized facts

3.1. Exploratory Spatial Data Analysis (ESDA)

Several statistical tests have been guiding the way to evaluate the existence of spatial dependence in a dataset. The most popular one is Moran's I test, which can be defined as:

$$I_x = \sum_i \sum_j w_{ij} \cdot (x_i - \mu) \cdot \frac{(x_j - \mu)}{\sum_i (x_i - \mu)^2} \tag{1}$$

where w_{ij} represents the spatial structure of the data, and it is constructed from a spatial weight matrix, x_i is the value of the variable x at location-i, x_j is the value of the same variable at location j, and μ is the cross-sectional mean of the data. Statistical inference for Moran's I can be implemented using either an assumption of normality or a simulation of a reference distribution based on random permutation (Anselin, 1995).

A local analysis of spatial autocorrelation compensates the analysis of global dependence by recognizing the specific location of spatial clusters and outliers. Specifically, local spatial patterns such as hot spots (relatively high values), cold spots (relatively low values), and spatial outliers (high values surrounded by low values and vice-versa) can be identified using the methods developed by (Anselin, 1995). The local version of Moran's I can be computed for each spatial unit defined as:

$$I_i = \frac{(x_i - \mu)}{\sum(x_i - \mu)^2} \sum_j w_{ij} \cdot (x_j - \mu) \tag{2}$$

where the notation follows that of Equation 1. Statistical inference is based on a conditional permutation approach. One of the most appealing features of an analysis of local spatial dependence is that statistically significant values can be plotted in a map. Thus, it greatly facilitates the spatial identification of high and low value clusters (hot spots and cold spots) and spatial outliers.

3.2. Geographically Weighted Regression (GWR)

This paper measured the uneven speed of night-time lights beta-convergence and the potential sources of this unevenness using GWR. GWR focuses on spatial heterogeneity and it enables the estimation of locally varying beta-coefficients (Brunsdon et al., 1996; Fotheringham et al., 2003). According to Darmofal (2015), it is advised that if spatial autocorrelation is present, spatial heterogeneous effects should be tested and modelled. As unmodeled spatial heterogeneity is a form of model misspecification. This paper identified the presence of spatial autocorrelation in night-time lights by using global Moran's I. And later tested for its heterogeneous effects by using Monte Carlo simulation following Ingram & da Costa (2019) and Lu et al. (2019). Both results provided firm support for the use of GWR. In the simplest form, GWR can be expressed as:

$$y_i = \beta_i X_i + \varepsilon_i \tag{3}$$

where, y_i is the growth of night-time lights from year 2012 to 2018 for district i, X_i is the initial night-time lights intensity in year 2012, and other conditional factors, ε_i is a random error term at location i, β_i is the vector of coefficient associated with the predictors in X for location i. Location i is captured by the longitude and latitude of the centroid of each district and the estimation of β_i is based on a kernel conditioned by other observations in the dataset (Ingram & da Costa, 2019). This paper is interested in the heterogeneous outcomes of the predictors i.e., positive effect for some districts, and negative effect for some districts, which significance levels are above the 5% conventional threshold.

3.3. Data

As seen in Table 2, regional development in this paper is measured through GDP growth and night-time lights satellite data across 147 districts (balanced dataset without missing values) in Sumatera over the 2012-2020 period. We use the change of access to the internet and the change of access to credit as our key explanatory variables. Following the original convergence regression of Solow growth model augmented with human capital and physical capital, we use the log initial value GDP and log initial value of night-time lights data to capture the economic activities and concentration across districts in Sumatera. We also append the control variables which are: change of population, change of investment share, and human capital. All data are obtained from the Central Bureau of Statistics of Indonesia.

Table 2. Data and sources

Name	Description	Source
Satellite night-time lights data	Sum of average night-time light in radiance (nW/cm2/sr)	Earth Observation Group
GDP growth	The change of GDP during 2012-2020	BPS
Change in access to internet	The difference of percentage household access internet in a district	BPS
Change in access to credit	The difference of percentage household access credit for business in a district	BPS
Change in investment share	The change of public investment ratio to GDP (percentage point)	BPS
Change in population	The change of number of populations between final and initial year (in person)	BPS
Human capital	The weighted index of education and health indicators	BPS

On another hand, the night-time lights data were obtained from the Suomi National Polar-orbiting Partnership (SNPP) Visible Infrared Imaging Radiometer Suite (VIIRS) Day-

Night Band (DNB) global monthly cloud-free radiance averages. And in specific, it is the grid 75N 60E of VIIRS night-time lights (VNL) version 2 with stray lights corrected by Elvidge et al. (2021), downloaded from Earth Observation Goup (mines.edu).

The growth of GDP and night-time lights data are stated as the dependent variable. As the preliminary diagnostics, we conduct the regression analysis to evaluate how much night-time lights data can explain the variation of GDP growth in the model (see Section 3.4).

Table 3. Descriptive statistics

Variable	Symbol	N	Min	Max	Mean	Std. Dev
Growth of Night-time lights data	g_Y_i	147	-0.540	2.240	0.565	0.448
Growth of GDP	g_GDP	147	-0.110	0.370	0.142	0.051
Log_initial year of night-time lights data (y=2012)	Log_Y2012	147	13.250	18.470	15.710	0.994
Log_initial year of GDP (y=2012)	Log_GDP2012	147	0.658	9.550	5.813	1.762
Change in access to internet	Chg_Internet	147	17.430	48.750	31.303	6.493
Change in access to credit	Chg_Credit	147	-8.640	31.370	12.485	7.316
Change in investment share	Chg_Inv	147	-0.400	0.030	-0.057	0.071
Change in population	Chg_Pop	147	2283	374427	42651.43	50814.12
Human capital	Capital	147	23.54	32.77	27.226	1.693

Source: Authors' calculation

3.4. Stylized facts

The Moran's scatter plot for per GDP and night-time lights in Fig.1 shows evidence of spatial heterogeneity, i.e., the co-existence of two distinct spatial regimes underlying the overall positive spatial association, with most of the districts in the HH (high-high) and LL (low-low) cluster. The Moran's I statistics at the initial year for GDP and night-time lights data provides the similar value, which is 0.39, while the values at final year are increasing with the satellite data providing the higher spatial autocorrelation coefficient. As the comparison, the pattern of Moran's scatter plot for GDP and night-time lights data shows us the similar tendencies to capture the spatial interaction, both on spatial association and heterogeneity across districts in Sumatera. Therefore, it can be said that night-time lights data could be a proxy for capturing the intensity and concentration of economic activities in Sumatera.

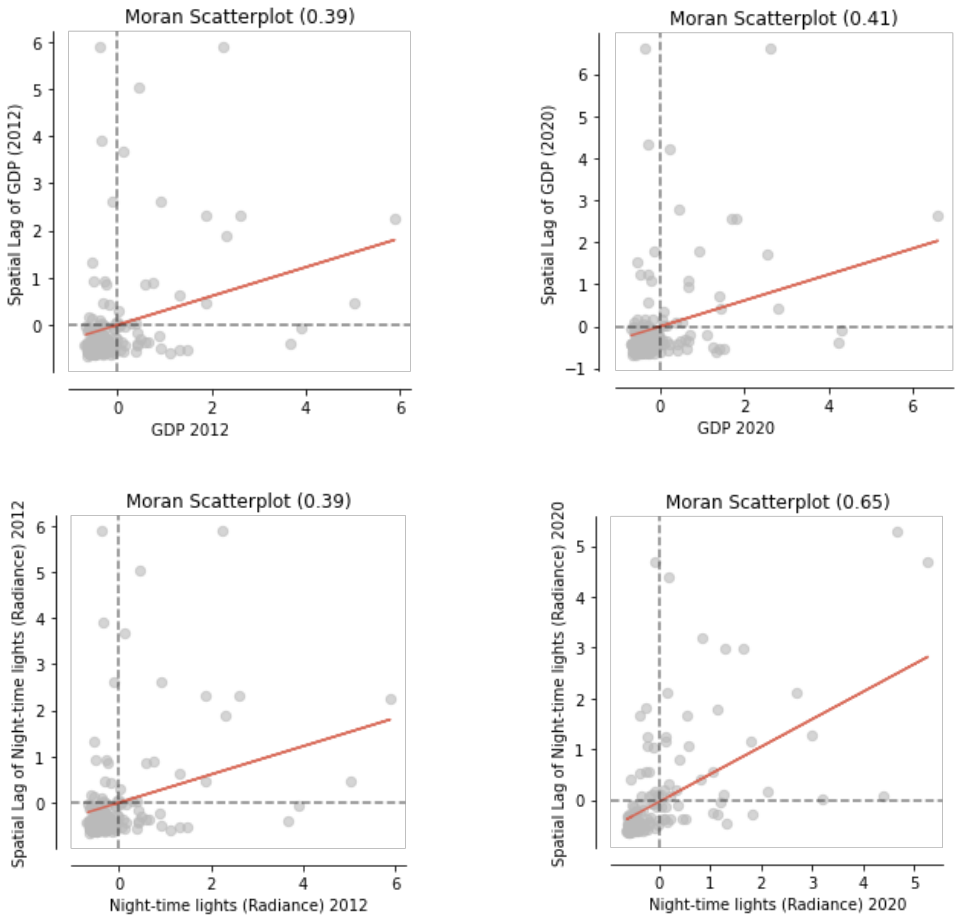


Figure 1. Moran's I scatter plot for GDP and night-time lights data (2012 and 2020)

The analysis of Local Indicator of Spatial Association (LISA) proposed by Anselin (1995) is beneficial for recognizing the location of spatial clusters and spatial outliers. Cold-spots and hot-spots are the spatial clusters in which spatial dependence is statistically significant. Cold-spots are spatial clusters with significantly low values, whereas hot-spots are spatial clusters with significantly high values.

From Figure 2, we can compare the pattern of spatial clusters and spatial outliers which are created from the data of GDP and night-lights data. The choropleth maps show the similar tendencies between GDP at the initial year (2012) with night-lights data at the initial year. Following, the more similar pattern is also found between the maps of GDP at the final year (2020) with night-lights at the final year. This finding support the portrait of Moran's I scatter plot as displayed in Figure 1. Thus, from the perspectives of spatial aspect, the variability of GDP can be explained by the night-lights data.

Districts in Sumatera Utara and Sumatera Selatan are two provinces which have persistent pattern of high level of GDP in both official and night-time lights data (hot-spots), while districts in Bengkulu always indicates persistent low-level of GDP in both official and night-time lights data (cold-spots).

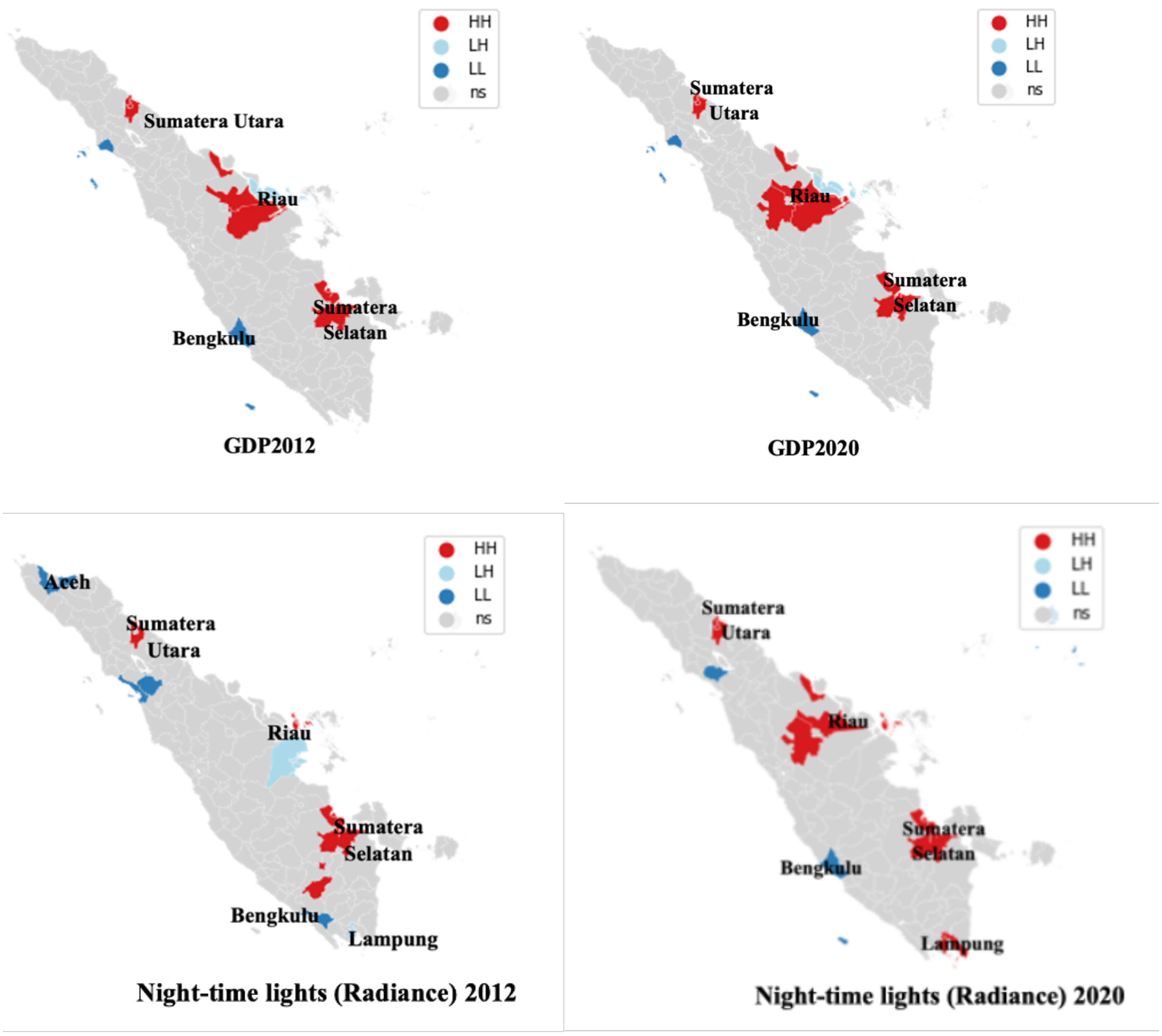


Figure 2. LISA for GDP and night-time lights (2012 and 2020)

Some literature argue that GDP can suffer from errors such as, making inference from a small sample size and PPP adjustment errors. Hence, it is useful to cross-check GDP against other sources if available. This paper explores night-time light intensity as an alternative proxy of economic output. Lights shine into space from the infrastructures at residential areas and business districts which are on at night. Regions with higher economic output levels tend to produce a higher light radiance. One of its biggest advantages for the case of Indonesia is its ability to capture the economic output produced by the informal sectors or economic activities that were not recorded by the official statistics (Elvidge et al., 2017; Henderson et al., 2012; Weil, 2014). In Fig. 3, we show that night-time lights data can explain around 47 percent of GDP across districts in Sumatera in 2012. For the year 2020, the explanatory power of satellite night-time lights data to GDP data is 77 percent. Overall, our numbers are similar to the results reported in previous studies in other locations (Mendez-Guerra & Santos-Marquez, 2020).

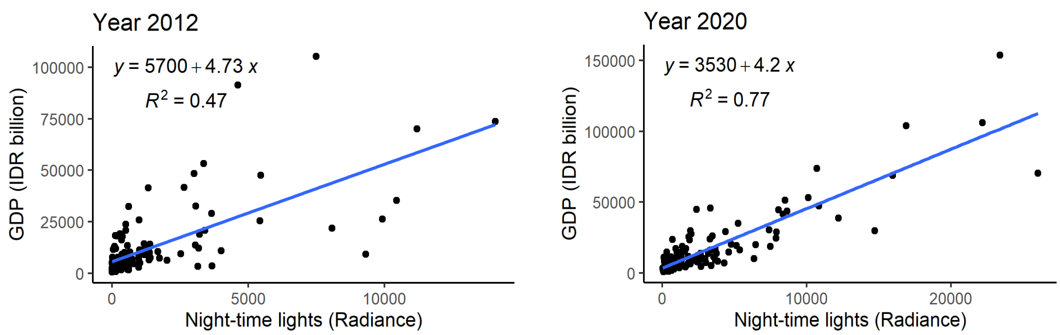


Figure 3. GDP as function of satellite data (2012 and 2020)

4. Results and discussion

4.1. Convergence estimation using OLS

This section discusses the findings of both unconditional and conditional convergence frameworks. Table 4 provides the results of convergence regression of satellite night-time lights data. As is known, based on the regression analysis, we have known that nightlight lights data can explain more than 70 percent the variability of GDP data (for the year 2020). This study contains data from a large data set of various backgrounds and characteristics across districts. Thus, conditional convergence is applied to cover the structural distinction and different institutions across districts. Three well-known predictors which have been widely used in sub-national growth studies are: human capital, population, and investment share. In addition, the use of internet access and access to credit are two key explanatory variables to measure the economic activities which are, in this case, approached by satellite data. The standard OLS convergence regression which is used in this paper is:

$$g\_Y_i = \beta_1 Log\_Y2012 + \beta_2 Chg\_Internet + \beta_3 Chg\_Credit + \beta_4 Chg\_Inv + \beta_5 Chg\_Pop + \beta_6 Capital + \varepsilon_i \quad (4)$$

The initial value of satellite night-time lights data has negative coefficient for both models, with and without conditional convergence. It implies that the catching-up process (convergence) has occurred, emphasizing that the smaller initial economic size regions tend to grow faster. By including control variables, especially change in access to the internet and change in access to credit, the log initial value of satellite data has a larger coefficient, implying that control variables tend to accelerate the catching-up process. Districts with higher light radiance (higher economic output level) grow slower than those with lower light radiance (lower economic output level).

In general, the estimated coefficients provide expected results. Specifically, change in access to the internet and human capital indicate the positive and significant effects on economic growth (Solow, 1956; Haini, 2019; Jiménez et al.,2014) while change in investment share and population also have positive but insignificant effects on economic growth. The speed of convergence of the light radiance in absolute convergence is 2.3 percent per year. At this speed, regional disparities in economic output level are expected to be halved in about 30 years. However, including control variables generates the faster speed at 2.6 percent per year. At this speed, the gap on economic size will be reduced by half in about 26 years.

Table 3. OLS estimation of convergence

Variables	Unconditional (Absolute Convergence)	Conditional Convergence
	Dependent Variable: Growth of light, 2012-2020	
Constant	1.525*** (0.122)	0.433 (0.425)
Lights in 2012 (log)	- 0.165*** (0.019)	- 0.190*** (0.018)
Change in access to internet	-	0.013*** (0.005)
Change in access to credit	-	- 0.0002 (0.004)
Change in investment share	-	0.507 (0.342)
Change in population	-	0.000 (0.000)
Human capital	-	0.031** (0.015)
R^2	0.42	0.49
Observation	147	147
Speed of convergence	0.023	0.026
Half-life (years)	30.72	26.30

Source: Authors' calculation

4.2. Convergence estimation using GWR

GWR allows the estimation of locally varying coefficients for predictors of interest and focuses on spatial heterogeneity. It opposes the spatial homogeneity that has been more common spatial error and spatial lag specifications (Anselin, 1988). We found spatial autocorrelation in the dependent variable, i.e., growth of night-time lights data (Moran's I = 0.65, $p < 0.05$), and then tested for heterogeneous effects. There are several ways to test for this heterogeneity. In this paper, we apply Monte Carlo simulations following Lu et al., (2019), and the results indicate firm support for our GWR approach. For these reasons, we do not implement spatial convergence framework using other conventional spatial models, but emphasize on examining spatial heterogeneity with GWR models.

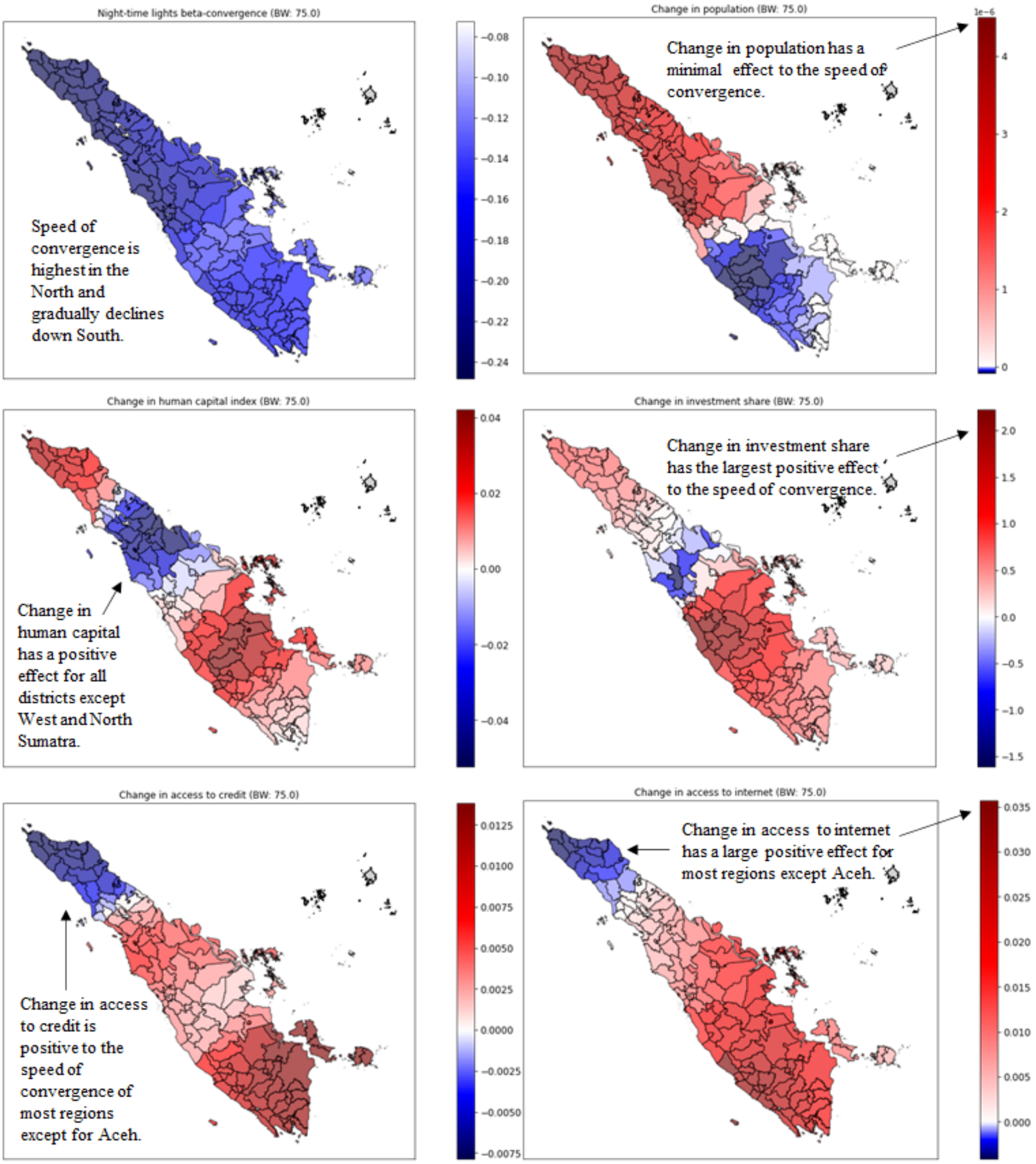
Based on the results of Monte Carlo for stationarity test reported in the Appendix 1, all variables – both independent and dependent variables – have spatially varying effect, including the initial level of lights (lights in 2012) both in absolute and conditional convergence models, change in access to internet ($p < 0.05$ in conditional convergence model), change in access to credit ($p < 0.\ 05$ in conditional convergence model), change in investment share ($p < 0.05$ in conditional convergence model), change in population ($p < 0.05$ in conditional convergence model), and human capital ($p < 0.10$). These results provide justification to apply GWR model. In addition, the results of local multicollinearity test show that there is no variable correlated each other (multicollinearity is not found).

Departing from equation 4, our GWR model specification can be written as:

$$g\_Y_i = \beta_{1i} Log\_Y2012_i + \beta_{2i} Chg\_Internet_i + \beta_{3i} Chg\_Credit_i + \beta_{4i} Chg\_Inv_i + \beta_{5i} Chg\_Pop_i + \beta_{6i} Capital_i + \varepsilon_i \quad (5)$$

where, g_Y_i is the growth of night-time lights from year 2012 to 2018 for district i, Log_Y2012 is the initial night-time lights intensity in year 2012, $Chg\_Internet$ is the change in access to internet for district i, Chg_Credit is the change in access to credit for district i, Chg_Inv is the change in investment share for district i, Chg_Pop is the change in population for district i, $Capital$ is human capital for district i and ε_i is a random error term at location i. β_i is the vector of coefficient associated with the predictors in the X for location i. Location i is captured by the longitude and latitude of the centroid of each district and the estimation of β_i is based on a kernel conditioned by other observations in the dataset.

Figure 4 shows the night-time lights conditional beta-convergence results and the conditioning factors for every district across Sumatera using GWR.



Note: The first grid shows that night-time lights are conditionally converging across all districts in Sumatera. The legend shows the beta coefficient or the degree at which the district is converging. The remaining grids show the magnitude of either positive or negative effect of a conditional factor to the speed of convergence.

Fig 4. GWR of Night-time light Unconditional and Conditional Convergence

In the first map, it was shown that there is spatial heterogeneity in the beta-convergence of night-time light intensity across the districts in Sumatera from the year 2012 to 2020. The maximum beta-coefficient is -0.24 and the minimum is -0.08. While the average beta-convergence coefficient across all districts is -0.19. The districts in the North are experiencing a higher convergence magnitude than the average, and the South a lower beta-convergence magnitude as compared to the average.

The second map shows that the change in population has a positive effect in Northern Sumatera and a slight negative effect for the districts in the South. The minimum and maximum coefficients for the change in population are around 0 to 0.000004. Following, the change in human capital index has about 0.02 to 0.04 positive effect in increasing the magnitude of conditional beta-convergence across all districts, except for West and North Sumatera at about -0.02 to -0.04. As for the change in investment share, it has the largest positive effect for beta-convergence and is largely beneficial for most districts. For instance, a point increase in investment share brings about 0.5 to 2.0 point increase in beta-convergence magnitude. Conversely, a point increase in investment share decreases the beta-convergence point by -0.5 to -1.5 for West and North Sumatera.

Lastly, change in access to credit has about 0.0025 to 0.0125 positive effect on beta-convergence for most districts in Sumatera, except Aceh. The negative effect is about -0.0025 to -0.0075. Similarly, the change in access to the internet has a large positive effect at 0.005 to 0.035 for most districts except Aceh, Nias Islands, and some districts in Riau Island (Kepulauan Natuna and Anambas). However, the negative effect of change in access to the internet is near 0.

4.3. Discussion

As mentioned before, districts in the northern area are experiencing a higher convergence magnitude than the average, and districts in the southern area have a lower beta-convergence magnitude as compared to the average. Therefore, one is easily tempted to conclude that districts in the northern area grow faster and then catch-up the high-income districts. However, this interpretation could be misleading. Not all districts in the northern area record high growth rate from 2012 to 2020. As can be seen from Figure 5, most districts in Aceh province record very low growth while districts in North Sumatera province indeed have relatively higher growth. Similarly, most districts in Riau province and some districts in South Sumatera province also report very low growth. When these spatially uneven growth rates are considered in interpreting the convergence speed from GWR results, the more appropriate conclusion would be that the convergence patterns across districts in Sumatera are heterogeneous. Income gap between districts in Aceh tend to decline relatively faster - or faster convergence speed - not necessarily because low-income districts grow faster than their high-income neighbors, but possibly due to substantially weakening performance in most high-income districts of Aceh. The somewhat similar story applies for the convergence patterns in Riau province. In contrast, districts in other provinces demonstrate clear convergence to higher income levels, most notably in North Sumatera, West Sumatera, Bengkulu, and Lampung provinces.

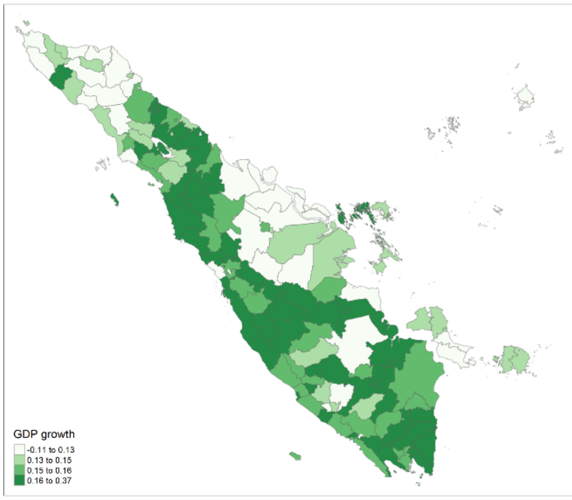


Figure 5. Growth rates of GDP from 2012 to 2020

The GWR results on access to credit and access to the internet are also worth noting. With regard to access to credit, it is reported that most districts in Sumatera gain benefit from increasing access to credit for households, except districts in Aceh province. This could be related to the fact that growth rates in Aceh province have been very low during the past 10 years. Interestingly, however, increasing access to credit is helpful for the growth rate in districts of Riau province albeit with relatively lower effects. Similarly, we are also able to document the effect of internet access on economic growth across districts in Sumatera. As expected, internet access has positive effects on growth for most regions. This is based on the endogenous growth model by Romer (1986, 1990) explaining that balanced growth is positively influenced by knowledge spillover. We hypothesize that the internet plays a great role in spreading knowledge in an economy. Therefore, economic growth is positively related with the use of the internet. Furthermore, our particular finding on the supportive role of access to the internet on economic growth echoes most of the evidence reported in previous studies (Antonopoulos & Sakellaris, 2009; Choi & Yi, 2009; Dedrick et al., 2003; Haini, 2019; Jiménez et al., 2014; Skordili, 2008). Nevertheless, we acknowledge the limitation of our data in accurately measuring the importance of the internet in promoting economic growth. In the future, when the data is made available, one could use more specific indicators to capture the productive usage of the internet for income, such as number e-commerce transactions at district level.

5. Conclusion and policy recommendation

Reducing regional inequalities is main concern for the sustainable development in Indonesia. Given the insular geography of Sumatera, uneven spatial distribution of natural resources, and region-specific patterns of production, inequalities in growth performance is an inevitable outcome in the Indonesian economy. This paper evaluates the growth convergence using satellite night-time lights data across 147 districts in Sumatera over the 2012-2020 period and the role of spatial heterogeneity in affecting the growth convergence in Sumatera. This paper also examines the magnitude of convergence with and without the inclusion of conditional (control) variables.

Our results show that regional growth convergence exists in both non-spatial and spatial framework. The inclusion of control variables accelerates the speed of convergence in OLS model. However, from the standpoint of spatial heterogeneity, we conclude that convergence pattern is different across regions. As such, the magnitude of convergence is also heterogeneous across districts. The maximum magnitude of convergence in GWR is greater than that of in OLS model. Overall, the northern parts of Sumatera generate a higher speed of convergence compared to the southern parts.

Using both OLS and GWR model, our findings show that access to internet is significant in affecting the growth convergence process in Sumatera. On average, the effect of internet is positive to boost the growth, while using GWR, the effect of internet access is positive, except in Aceh provinces, Kepulauan Nias, and some districts in Kepulauan Riau (Kepulauan Natuna and Anambas). The similar portrait also occurs in credit access. On average, the effect of credit is negative to growth convergence. Analysing beyond the average using GWR, the effect is also diverse. The positive effect of credit are mostly seen along the middle and southern parts of Sumatera (Riau, Sumatera Selatan, Lampung, Bengkulu), insignificant in a few districts in Sumatera Utara, and negative in all districts in Aceh. Therefore, the application of GWR to capture phenomena in heterogeneous geography is beneficial to identify and design spatially diverse-based development plan.

Our results of heterogeneity from GWR give rise to the importance of designing regional development policies in at least two following fronts. *First*, regional development policies should be designed to be diverse across districts. *One-size-fits-all* policy is not desirable for promoting equal growth in Sumatera due to the existence of spatial heterogeneity. *Second*, policies should target to increase the utility of digitalization and internet penetration for productive activities in order to support the economy in new normal era of COVID-19.

Finally, some caveats in this paper call for particular concerns. First, the variable of internet access in this paper does not necessarily reflect the use of internet for economic activities. For future research, it is advisable to use variable that represent productive usage of internet such as e-commerce transaction at district level.[2] Second, the use of variable that represent telecommunication infrastructure at the district level could also enrich and provide more comprehensive analyses for further investigation. Lastly, the findings of insignificant effect of internet access on growth in entire parts of Aceh province require further exploration.

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2 To the best of our knowledge, at this moment e-commerce transaction data is not available at district level.

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APPENDICES

Appendix A. Monte Carlo Stationary Test

Variables	Unconditional Convergence (only using Log_Y2012 as independent variables)	Conditional Convergence (with all determinants)
Constant	0.000	0.000
Log_Night-time lights in 2012	0.029	0.003
Change in access to internet	-	0.001
Change in access to credit	-	0.032
Change in investment share	-	0.007
Change in population	-	0.009
Human capital	-	0.053

Note: values reported are p-values
Number of simulations: 1000

We use online interactive computation frameworks that make possible for everyone (with access) to replicate most of the results in this paper.

Appendix B. Online computation notebooks

Computation	Link
Exploratory Spatial Data Analysis (ESDA)	https://deepnote.com/@ragdad-cani-miranti/Regional-Growth-Convergence-and-Heterogeneity-0wDJ9O-VQw28ZThpRb8-tQ
Geographically Weighted Regression (GWR)	https://deepnote.com/@siew-sook-yan/Python-Geographically-Weighted-Regression-GWR-vwNhTvvvTwe9W8iumNFSaw

Appendix C. Local Multicollinearity Test (Local VIF)

District	local_CN	local_vif_credit_chg	local_vif_chg_Internet	local_vif_human_capital	local_vif_inv_chg	local_vif_pop_chg
Kabupaten Aceh Singkil	2.051	1.363	1.219	1.081	1.206	1.071
Kabupaten Aceh Selatan	2.128	1.383	1.233	1.098	1.223	1.068
Kabupaten Aceh Tenggara	2.146	1.386	1.235	1.096	1.222	1.070
Kabupaten Aceh Timur	2.206	1.404	1.253	1.111	1.235	1.068
Kabupaten Aceh Tengah	2.162	1.392	1.246	1.110	1.232	1.066
Kabupaten Aceh Barat	2.146	1.387	1.244	1.114	1.231	1.064
Kabupaten Aceh Besar	2.231	1.388	1.252	1.121	1.233	1.064
Kabupaten Pidie	2.188	1.391	1.250	1.117	1.233	1.065
Kabupaten Bireuen	2.185	1.398	1.254	1.117	1.235	1.066
Kabupaten Aceh Utara	2.194	1.402	1.254	1.115	1.236	1.067
Kabupaten Aceh Barat Daya	2.135	1.386	1.239	1.107	1.229	1.066
Kabupaten Gayo Lues	2.165	1.392	1.242	1.104	1.229	1.068
Kabupaten Aceh Tamiang	2.216	1.404	1.251	1.106	1.233	1.070
Kabupaten Nagan Raya	2.138	1.386	1.242	1.110	1.230	1.065
Kabupaten Aceh Jaya	2.187	1.387	1.249	1.119	1.232	1.064
Kabupaten Bener Meriah	2.173	1.395	1.249	1.113	1.234	1.066
Kabupaten Pidie Jaya	2.177	1.392	1.250	1.116	1.233	1.065
Kota Banda Aceh	2.228	1.389	1.252	1.121	1.233	1.064
Kota Sabang	2.243	1.390	1.253	1.121	1.233	1.064
Kota Langsa	2.214	1.404	1.252	1.108	1.234	1.069
Kota Lhokseumawe	2.192	1.401	1.254	1.115	1.236	1.067
Kota Subulussalam	2.112	1.377	1.229	1.087	1.209	1.072
Kabupaten Mandailing Natal	2.897	1.222	1.276	1.027	1.082	1.155
Kabupaten Tapanuli Selatan	2.356	1.265	1.257	1.044	1.095	1.118
Kabupaten Tapanuli Tengah	2.048	1.300	1.238	1.057	1.122	1.097
Kabupaten Tapanuli Utara	2.148	1.307	1.245	1.063	1.122	1.097
Kabupaten Toba Samosir	2.157	1.337	1.245	1.076	1.145	1.090
Kabupaten Labuhan Batu	2.710	1.288	1.269	1.068	1.104	1.111
Kabupaten Asahan	2.252	1.349	1.252	1.087	1.154	1.089
Kabupaten Simalungun	2.198	1.381	1.244	1.093	1.190	1.080
Kabupaten Dairi	2.140	1.380	1.233	1.088	1.207	1.074
Kabupaten Karo	2.160	1.385	1.236	1.091	1.212	1.073
Kabupaten Deli Serdang	2.223	1.398	1.246	1.098	1.220	1.074

Kabupaten Langkat	2.214	1.401	1.248	1.103	1.229	1.071
Kabupaten Humbang Hasundutan	2.081	1.359	1.233	1.080	1.174	1.081
Kabupaten Pakpak Bharat	2.109	1.374	1.230	1.085	1.199	1.075
Kabupaten Samosir	2.126	1.369	1.236	1.084	1.182	1.080
Kabupaten Serdang Bedagai	2.240	1.397	1.249	1.099	1.210	1.076
Kabupaten Batu Bara	2.257	1.384	1.253	1.103	1.187	1.080
Kabupaten Padang Lawas Utara	2.891	1.253	1.282	1.040	1.086	1.137
Kabupaten Padang Lawas	3.405	1.227	1.302	1.027	1.085	1.172
Kabupaten Labuhan Batu Selatan	3.180	1.250	1.295	1.039	1.086	1.147
Kabupaten Labuhan Batu Utara	2.338	1.313	1.255	1.072	1.123	1.099
Kota Sibolga	2.030	1.311	1.236	1.059	1.131	1.094
Kota Pematang Siantar	2.265	1.347	1.253	1.088	1.152	1.090
Kota Tebing Tinggi	2.189	1.379	1.243	1.090	1.189	1.080
Kota Medan	2.233	1.392	1.248	1.097	1.203	1.078
Kota Binjai	2.218	1.398	1.246	1.098	1.220	1.073
Kota Padangsidimpuan	2.205	1.397	1.244	1.098	1.221	1.072
Kota Gunungsitoli	2.474	1.254	1.263	1.040	1.088	1.125
Kabupaten Pesisir Selatan	3.957	1.112	1.357	1.163	1.214	1.432
Kabupaten Solok	4.654	1.114	1.414	1.112	1.192	1.463
Kabupaten Sijunjung	4.703	1.117	1.435	1.102	1.181	1.470
Kabupaten Tanah Datar	5.831	1.131	1.442	1.061	1.198	1.456
Kabupaten Padang Pariaman	6.107	1.132	1.417	1.058	1.210	1.439
Kabupaten Agam	6.498	1.154	1.433	1.037	1.230	1.430
Kabupaten Lima Puluh Kota	6.120	1.152	1.451	1.041	1.204	1.428
Kabupaten Pasaman	5.465	1.193	1.357	1.018	1.143	1.280
Kabupaten Solok Selatan	3.148	1.113	1.341	1.198	1.211	1.434
Kabupaten Dharmasraya	3.073	1.110	1.352	1.191	1.198	1.445
Kabupaten Pasaman Barat	4.874	1.184	1.315	1.017	1.111	1.236
Kota Padang	5.018	1.115	1.397	1.103	1.199	1.445
Kota Solok	4.860	1.117	1.411	1.099	1.190	1.447
Kota Sawah Lunto	5.037	1.120	1.426	1.089	1.186	1.454
Kota Padang Panjang	5.961	1.135	1.424	1.056	1.202	1.435
Kota Bukittinggi	6.254	1.147	1.430	1.043	1.212	1.426

Kota Payakumbuh	5.931	1.144	1.439	1.048	1.195	1.426
Kota Pariaman	6.127	1.133	1.403	1.057	1.211	1.424
Kabupaten Kuantan Singingi	4.210	1.116	1.437	1.114	1.166	1.471
Kabupaten Indragiri Hulu	3.078	1.102	1.372	1.170	1.167	1.461
Kabupaten Indragiri Hilir	2.299	1.059	1.283	1.204	1.145	1.425
Kabupaten Pelalawan	3.891	1.120	1.416	1.124	1.146	1.454
Kabupaten Siak	4.717	1.176	1.442	1.072	1.143	1.377
Kabupaten Kampar	5.305	1.149	1.449	1.057	1.169	1.408
Kabupaten Rokan Hulu	4.627	1.228	1.357	1.022	1.116	1.226
Kabupaten Bengkalis	4.485	1.223	1.425	1.081	1.142	1.321
Kabupaten Rokan Hilir	3.795	1.258	1.316	1.052	1.091	1.153
Kabupaten Kepulauan Meranti	3.599	1.165	1.391	1.126	1.123	1.388
Kota Pekanbaru	5.148	1.170	1.450	1.056	1.158	1.379
Kota Dumai	5.208	1.277	1.441	1.053	1.169	1.248
Kabupaten Kerinci	2.588	1.132	1.221	1.275	1.255	1.279
Kabupaten Merangin	2.465	1.128	1.212	1.274	1.250	1.255
Kabupaten Sarolangun	2.547	1.107	1.169	1.250	1.270	1.131
Kabupaten Batang Hari	2.220	1.051	1.224	1.212	1.221	1.268
Kabupaten Muaro Jambi	2.184	1.029	1.236	1.215	1.218	1.282
Kabupaten Tanjung Jabung Timur	2.121	1.023	1.260	1.240	1.201	1.348
Kabupaten Tanjung Jabung Barat	2.158	1.052	1.265	1.208	1.180	1.385
Kabupaten Tebo	2.381	1.096	1.293	1.217	1.194	1.402
Kabupaten Bungo	2.586	1.113	1.290	1.232	1.218	1.389
Kota Jambi	2.188	1.024	1.239	1.219	1.222	1.278
Kota Sungai Penuh	2.736	1.128	1.239	1.265	1.250	1.308
Kabupaten Ogan Komering Ulu	2.320	1.026	1.164	1.169	1.103	1.143
Kabupaten Ogan Komering Ilir	2.471	1.008	1.163	1.212	1.116	1.175
Kabupaten Muara Enim	2.279	1.027	1.171	1.163	1.114	1.136
Kabupaten Lahat	2.397	1.059	1.176	1.144	1.112	1.105
Kabupaten Musi Rawas	2.813	1.086	1.190	1.191	1.203	1.076
Kabupaten Musi Banyuasin	2.406	1.026	1.204	1.196	1.221	1.125
Kabupaten Banyu Asin	2.357	1.005	1.213	1.214	1.163	1.185

Kabupaten Ogan Komering Ulu Selatan	2.330	1.036	1.162	1.167	1.090	1.141
Kabupaten Ogan Komering Ulu Timur	2.376	1.019	1.158	1.184	1.103	1.155
Kabupaten Ogan Ilir	2.372	1.010	1.171	1.192	1.122	1.163
Kabupaten Empat Lawang	2.605	1.079	1.179	1.146	1.140	1.085
Kabupaten Penukal Abab Lematang Ilir	2.254	1.022	1.179	1.168	1.133	1.135
Kabupaten Musi Rawas Utara	2.851	1.113	1.172	1.256	1.292	1.075
Kota Palembang	2.383	1.006	1.186	1.204	1.138	1.173
Kota Prabumulih	2.296	1.019	1.172	1.172	1.119	1.144
Kota Pagar Alam	2.376	1.061	1.176	1.141	1.108	1.106
Kota Lubuklinggau	2.833	1.094	1.185	1.187	1.199	1.072
Kabupaten Bengkulu Selatan	2.428	1.074	1.178	1.134	1.108	1.097
Kabupaten Rejang Lebong	2.848	1.100	1.184	1.183	1.193	1.069
Kabupaten Bengkulu Utara	2.554	1.106	1.184	1.126	1.116	1.080
Kabupaten Kaur	2.298	1.061	1.176	1.143	1.091	1.117
Kabupaten Seluma	2.600	1.088	1.179	1.140	1.133	1.082
Kabupaten Mukomuko	2.686	1.147	1.170	1.314	1.282	1.182
Kabupaten Lebong	3.028	1.154	1.158	1.296	1.296	1.060
Kabupaten Kepahiang	2.865	1.108	1.184	1.179	1.186	1.066
Kabupaten Bengkulu Tengah	2.938	1.121	1.184	1.191	1.196	1.060
Kota Bengkulu	2.962	1.128	1.184	1.192	1.195	1.058
Kabupaten Lampung Barat	2.347	1.035	1.160	1.171	1.088	1.144
Kabupaten Tanggamus	2.419	1.027	1.148	1.191	1.087	1.158
Kabupaten Lampung Selatan	2.514	1.018	1.141	1.214	1.094	1.173
Kabupaten Lampung Timur	2.527	1.014	1.143	1.217	1.098	1.175
Kabupaten Lampung Tengah	2.488	1.015	1.147	1.209	1.099	1.171
Kabupaten Lampung Utara	2.417	1.021	1.150	1.191	1.095	1.160
Kabupaten Way Kanan	2.382	1.022	1.155	1.183	1.097	1.154
Kabupaten Tulangbawang	2.520	1.012	1.148	1.216	1.103	1.176
Kabupaten Pesawaran	2.470	1.020	1.144	1.204	1.092	1.167
Kabupaten Pringsewu	2.445	1.022	1.146	1.198	1.091	1.163
Kabupaten Mesuji	2.505	1.010	1.155	1.215	1.109	1.177
Kabupaten Tulang Bawang Barat	2.458	1.014	1.151	1.203	1.103	1.169
Kabupaten Pesisir Barat	2.361	1.037	1.156	1.173	1.084	1.147

Kota Bandar Lampung	2.484	1.019	1.143	1.207	1.093	1.169
Kota Metro	2.491	1.016	1.144	1.209	1.096	1.171
Kabupaten Bangka	2.743	1.037	1.262	1.302	1.168	1.239
Kabupaten Belitung	3.049	1.030	1.187	1.313	1.121	1.229
Kabupaten Bangka Barat	2.626	1.030	1.270	1.287	1.180	1.233
Kabupaten Bangka Tengah	2.800	1.023	1.211	1.286	1.140	1.223
Kabupaten Bangka Selatan	2.829	1.019	1.186	1.281	1.127	1.217
Kabupaten Belitung Timur	3.126	1.034	1.184	1.323	1.118	1.233
Kota Pangkal Pinang	2.775	1.030	1.234	1.293	1.152	1.230
Kabupaten Karimun	2.617	1.110	1.282	1.225	1.107	1.418
Kabupaten Bintan	3.136	1.153	1.281	1.563	1.141	1.409
Kabupaten Natuna	4.094	1.280	1.249	1.771	1.117	1.396
Kabupaten Lingga	2.588	1.057	1.270	1.347	1.162	1.407
Kabupaten Kepulauan Anambas	3.645	1.253	1.176	1.716	1.102	1.428
Kota Batam	2.675	1.098	1.238	1.290	1.108	1.416
Kota Tanjung Pinang	2.839	1.098	1.222	1.368	1.115	1.418