Regional Convergence and Spatial Dependence across Subnational Regions in ASEAN:

Evidence from Satellite Nighttime Light Data

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(Version-20200624)

Abstract Satellite nighttime light data are increasingly used for evaluating the performance of economies in which official statics are non-existent, limited, or non-comparable. In this paper, we use a novel luminosity-based measure of GDP per capita to study regional convergence and spatial dependence across 274 subnational regions of the Association of South East Asian Nations (ASEAN) over the 1998-2012 period. Specifically, we first evaluate the usefulness of this new luminosity indicator in the context of ASEAN regions. Results show that almost 60 percent of the differences in (official) GDP per capita can be predicted by this luminosity-based measure of GDP. Next, given its potential usefulness for predicting regional GDP, we evaluate the spatio-temporal dynamics of regional inequality across ASEAN. Results indicate that although there is an overall (average) process of regional convergence, regional inequality within most countries has not significantly decreased. When evaluating the patterns of spatial dependence, we find increasing spatial dependence over time and stable spatial clusters (hotspots and coldspots) that are located across multiple national boundaries. Taken together, these results provide a new and more disaggregated perspective of the integration process of the ASEAN community.

Keywords convergence · spatial dependence · satellite nighttime light data · luminosity · subnational regions · ASEAN

JEL Classifications R10 · R11 · O57

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1 Introduction

Economic integration is a central priority of the development agenda of the Association of Southeast Asian Nations (ASEAN). As suggested by the experience of other economic communities, such the European Union, achieving economic integration goes hand in hand with the reduction of income disparities across countries as well as subnational regions within countries. Economic growth in ASEAN, however, has not been fully inclusive when considering the large income disparities that remain across countries and subnational regions of the ASEAN community. For example, the GDP per capita in Singapore is more than 13 times larger than that of Cambodia, Laos or Myanmar. Thus, it may seem that much needs to be done to close the income disparities within an economic community that has been on the quest for regional integration since 1967.

Given that the ASEAN community is conformed by only ten countries,[1] many previous studies are largely constrained by a small sample size problem. This constrain is particularly binding for the analyses of economic convergence and spatial dependence, which typically require a larger sample size to correctly infer the evolution of economic disparities over time and space. To increase the sample size, one could try to evaluate economic disparities among subnational regions instead of countries. A major difficulty, however, is the availability and comparability of regional data for developing countries.

In an attempt to overcome these data issues, economists have been using satellite nightlight data as proxy for economic activity. This approach has proved useful for evaluating the performance of economies in which official statics are non-existent, limited, or non-comparable. Motivated by the progress in this area of research, the aim of this paper is to evaluate the dynamics of convergence and spatial dependence across the subnational regions of the ASEAN community. In particular, we use the new regional income dataset of Lessmann and Seidel (2017) that has been constructed based on satellite nighttime light data. This dataset covers 274 ASEAN regions over the 1998-2012 period, and thus it provides a much larger sample size for evaluating convergence and spatial dependence.

[1] These are Indonesia, Malaysia, Philippines, Singapore, Thailand, Brunei, Laos, Myanmar, Cambodia and Vietnam.

In this paper, we first provide an overview of relationship between night-light luminosity intensity and GDP per capita for a sample of ASEAN regions where official GDP data is available. Results indicate that almost 60 percent of the differences in (official) GDP per capita can be predicted by a luminosity-based measure of GDP per capita.[2] Next, we use luminosity-based GDP per capita as a proxy for regional income and evaluate the spatio-temporal dynamics of regional inequality across the entire sample of 274 ASEAN sub-national regions over the 1998-2012 period. Results indicate that although—on average—there is regional convergence, regional inequality has not significantly decreased within most countries. Finally, we evaluate patterns of global and local spatial dependence across regions and countries. Results indicate increasing spatial dependence over time and the existence of stable spatial clusters beyond national borders.

The results of this paper contribute to the literature of regional convergence and spatial dependence in ASEAN in three fronts. First, we use a novel luminosity-based measure of GDP per capita to study the dynamics of convergence across a large sample of subnational regions in ASEAN. Second, to the best of our knowledge, this is the first study that systematically compares—within-country—regional convergence for nine ASEAN countries. Third, also to the best of our knowledge, this is the first study that evaluates spatial dependence and spatial clusters for multiple countries in ASEAN.

The rest of the paper is organized as follows. Section 2 provides an overview of the related literature. Section 3 describes the luminosity data and the methods of regional convergence and spatial dependence. Section 4 presents the results in three parts: usefulness of luminosity-based GDP data, regional convergence patterns, and spatial dependence patterns. Section 5 discusses related policy implications. Lastly, section 6 offers some concluding remarks.

2 Related literature

[2] To avoid confusion of terms, it is important to distinguish the difference among official GDP, luminosity intensity, and luminosity-based GDP. Lessmann and Seidel (2017) first estimate an econometric model that summarizes the relationship between GDP and luminosity intensity using a relatively small sample for which official GDP data is available. Second, based on this model, they carry out an out-of-sample prediction of GDP for a large number of subnational regions. This out-of-sample prediction is refereed as luminosity-based GDP.

2.1 Measuring economic activity using satellite nighttime light data

Satellite nighttime light data are increasingly used for evaluating the performance of economies in which official statics are non-existent, limited, or non-comparable (Chen and Nordhaus 2011; Nordhaus and Chen 2015; Henderson et al 2012; Lessmann and Seidel 2017; Mveyange 2018). Across countries, Henderson et al (2012) show a strong and largely significant relationship between changes in nighttime light intensities and economic growth. The interpretation of this strong relationship is simple: most economic activities that take place at night require light. Thus, one can expect that the higher a country's luminosity intensity at nighttime, the higher its level of economic activities. Ultimately, these differences in economic activities will also reflect differences in production capacity and income levels.

Henderson et al (2012) and Chen and Nordhaus (2011) also emphasize the usefulness of satellite nighttime light data at both subnational and supranational levels. As a result, a growing number of papers have been using satellite nighttime light data to uncover new and interesting patterns. For instance, Henderson et al (2012) find that coastal areas do not grow faster than non-coastal areas in sub-Saharan Africa. Alesina et al (2016) construct a new measure of ethnic inequality (based on nighttime luminosity) and find a strong inverse relationship between this measure of inequality and the level of development across subnational regions. Mveyange (2015) uses night lights data as proxy for subnational income in Africa. He finds increasing regional inequality between 1992 and 2003 and decreasing inequality between 2004 and 2012.

Lessmann and Seidel (2017) is one of the most comprehensive studies that uses satellite nighttime light data for understanding income differences within subnational regions in the world. They first use luminosity intensity data to predict regional GDP per capita within 180 countries over the 1992–2012 period. Based on this luminosity-based GDP, they study worldwide regional convergence and find that approximately 67 to 70 percent of all countries have reduced their subnational disparities, in other words, they have experienced within-country (sigma) convergence. They also find an N-shaped relationship between regional inequality and economic development. Finally, using cross-country data, they study the determinants of regional inequality and find that natural resources, transportation costs, trade openness, aid, federalism and human capital are significantly correlated with regional inequality.

2.2 Testing for economic convergence

Standard neoclassical growth theory predicts that when economies share common technological and institutional environments, less developed regions would tend to grow faster than more developed ones. As a result, a catch-up (convergence) process would take place and regional inequalities would tend to diminish (Abreu 2019). In the growth and development literature, this inverse relationship between the initial level of development of an economy and its subsequent growth rate is known as beta convergence (Barro and Sala-i Martin 1992; Sala-i Martin 1996; Magrini 2004).

A large number of studies have documented the existence of beta convergence in different contexts: countries, regions, industries, and firms. In particular, seminal contributions to the regional convergence literature, such as those of Barro and Sala-i Martin (1991, 1992), have pointed out that the estimated speed of convergence is surprisingly similar across multiple studies in the US, Japan, and Europe. A common finding has been that regional economies have tended to converge at a speed of two percent per year. This speed of convergence implies that, relative to a convergence equilibrium, the average region would close 50 percent of its income gap in about 35 years.

There is a growing literature about income convergence among ASEAN countries. The results so far, however, appear mixed and inconclusive. For instance, Ismail (2008) finds evidence of convergence for five ASEAN countries during the 1960-2004 period. Similarly, Solarin et al (2014) finds signs of convergence between 1970 and 2009. In contrast, other authors, such as Park (2000) and Alavi and Ramadan (2008), indicate no evidence of income convergence.[3]

Given the small sample size in terms of the number of countries that belong to ASEAN, most previous studies have employed time series analyses to study cross-country convergence. Specifically, it has been common to use unit root tests to evaluate convergence, first in the context of the five

[3] Besides income variables, convergence of other measures is also common in the literature. For instance, Mishra and Smyth (2014) reports robust ASEAN convergence in energy consumption per capita over the 1971-2011 period. Chong et al (2017) studies the evolution of sectorial production differences and finds that the newest members of ASEAN are catching up with the old members.

founding members of ASEAN and then in the entire ten-country sample.[4] The evaluation of convergence across subnational regions of ASEAN not yet been explored due lack of comparable data. In this context, the new dataset of Lessmann and Seidel (2017) provides a unique opportunity to evaluate convergence within and among the subnational regions of ASEAN and other supranational associations in the world (Breinlich et al 2014).

2.3 Evaluating spatial dependence

New economic geography theories emphasize that the dynamics of regional inequality have a spatial nature (Krugman 1998, 2011; Schmutzler 1999). This is largely due to the spatial concentration of economic activity and the diffusion of spillover effects beyond administrative borders. To start an evaluation of regional dynamics that could be reflecting any (or both) of these two spatial processes, an exploratory analysis of spatial dependence is highly recommended (Anselin et al 2007; Anselin 1999, 1995). In particular, global and local analyses of spatial association are useful for testing the hypothesis of spatial dependence and for identifying the location of spatial clusters and outliers.

Anselin et al (2007) emphasize that exploratory spatial data analysis (ESDA) methods can be particularly useful for maximizing the informational content of newly available subnational databases. These methods provide a basis for a spatially explicit policy that may be able to address the needs of individual regions more effectively than non-spatial analyses. Also, as software for spatial analysis continues to improve and new databases continue to emerge, there will be increasing opportunities to better monitor socio-economic activities within and between geographical units.

A central component of ESDA is the notion of spatial dependence. At its basic level, it refers to a phenomenon in which attribute similarity (for instance, similar values of income per capita across regions) is matched with locational similarity (that is, observations are located in geographical proximity). From a measurement standpoint, spatial dependence is commonly evaluated based on global and local indicators of spatial autocorrelation (Anselin (1995)). On the one hand, indicators of global spatial autocorrelation are helpful for evaluating the existence of an overall pattern of spatial clustering. On

[4] See, for instance, Chowdhury et al (2005); Jayanthakumaran and Lee (2008, 2013); Lim and McAleer (2004); Lee et al (2005); Solarin et al (2014); Rath (2019).

the other, local indicators of spatial autocorrelation are helpful for identifying the specific location of clusters and outliers.

To the best of our knowledge, we could not find any study that evaluates spatial income dependence across multiple ASEAN countries. It seems evident that study of spatial dependence across the subnational regions of ASEAN is highly constrained by the availability of comparable income data. However, studies for the subnational regions of individual countries are relatively more abundant. In particular, complex geographies such as those of Indonesia and Philippines are frequently evaluated through the lens of global and local indicators of spatial autocorrelation.[5]

3 Data and methods

This section describes the data and methodologies to evaluate spatio-temporal dynamics across the subnational regions of the ASEAN community. In the context of the research objectives, Figure 1 provides a workflow overview of the data and methods described in this section. We first describe the luminosity dataset in the context of ASEAN subnational regions. Next, we describe two methodologies to study regional convergence. Finally, we describe two methodologies to study spatial dependence.

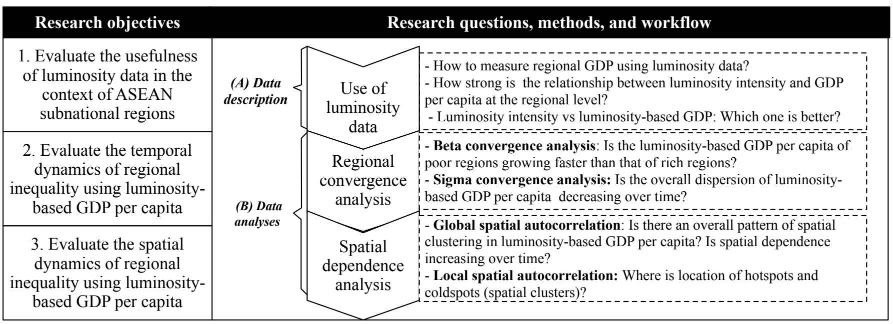


Fig. 1: Research workflow: Objectives, questions, data, and methods

[5] For instance, Rinaldi et al (2010) and Miranti and Mendez (2020) study the spatial dependence patterns of the human development index across provinces in Indonesia. For the Philippines, Salvacion (2020) studies spatial dependence of poverty rates across villages of the Marinduque Island; and Salvacion and Magcale-Macandog (2015) study spatial dependence of population growth in the same island.

3.1 Measuring regional GDP with luminosity data

A new luminosity dataset for a large sample of regions of the world has been originally assembled by Lessmann and Seidel (2017). These authors measure nighttime light intensities based on the satellite data from the U.S Air Force. Specifically, they use the satellite data that has been processed by the the Atmospheric Administration (NOAA) and the National Geophysical Data Center (NGDC). The scale of luminosity intensity is a number between 0 (no light) and 63 (full light) for every output pixel, which, at the equator, is approximately 0.86 square kilometers. The censoring of the of luminosity scale at 63 poses some problems for a few small rich areas. In case of Singapore, for instance, satellites are not able to identify within-country variation in luminosity. Thus, the subnational regions of Singapore are not included in this dataset.

In contrast to some previous studies, Lessmann and Seidel (2017) do not use luminosity intensity as a direct proxy for regional GDP. Instead, they first estimate an econometric model of the relationship between luminosity intensity and regional GDP for those countries in which subnational data are available. Next, given the estimated parameters of their econometric model and the availability of luminosity intensity data for a larger sample of subnational regions, they are able to estimate a luminosity-based measure of GDP per capita for 3.166 subnational regions of 180 countries over the 1992-2012 period.

Lessmann and Seidel (2017) provide estimates of luminosity-based GDP per capita for 3.166 first-level subnational administrations in 180 countries. Administrative boundaries data are from the Global Administrative Areas (GADM) project. Some examples of first-level subnational regions would be states, provinces, prefectures in the US, Indonesia, and Japan, respectively.

In this paper, we use the dataset of Lessmann and Seidel (2017) to study convergence and spatial dependence across the subnational regions of the Association of Southeast Asian Nations (ASEAN). After organizing this dataset in a way that is suitable for these two analyses, we end up with a dataset that covers 274 subnational regions of ASEAN for each year between 1998 and 2012. To briefly summarize this dataset, Table 1 provides some descriptive statistics for some selected years. In addition, Appendix B provides a list of the subnational regions of each country that is included in the dataset.

Table 1: Luminosity-based GDP per capita across 274 subnational regions of ASEAN

Year	1998	2002	2007	2012
Mean	3,926	4,336	5,295	6,074
Std.Deviation	4,935	5,129	5,400	5,445
Min	562	702	1,054	1,263
Q1	1,899	2,078	2,527	2,891
Median	2,768	2,978	3,642	4,209
Q3	4,757	5,380	6,842	8,029
Max	49,808	50,754	51,215	47,855
MAD	2,571	2,693	2,737	2,824
IQR	2,856	3,299	4,303	5,118
CV	1.26	1.18	1.02	0.90
Skewness	5.77	5.40	4.48	3.70
Kurtosis	41.97	37.68	28.09	19.87
Observations	274	274	274	274

Note: Q1 and Q3 stand for the first and third quartile of the distribution, respectively. MAD stands for the mean absolute deviation. IQR stands for the interquartile range. CV stands for the coefficient of variation.

Table 1 help us understand at least four initial features about the evolution of GDP per capita across subnational regions in ASEAN. First, indicators of centrality, such as the mean and median, consistently indicate that (luminosity-based) GDP per capita has increased over time, with a particular acceleration in more recent years. Second, there are large disparities in GDP per capita across subnational regions in ASEAN. In 2012, for instance, GDP per capita in the richest region of the sample was almost 38 times larger than that in the poorest region. Third, common indicators of dispersion, such as the standard deviation and the coefficient of variation, do not provide a conclusive answer on the evolution of regional disparities. On the one hand, the standard deviation would suggest that regional disparities have increased over time. On the other, the coefficient of variation would suggest a notable decrease. Forth, based on the skewness indicator, this inconclusive answer largely depends on the highly asymmetric shape the distribution of GDP per capita across subnational regions.[6]

The descriptive statistics of Table 1 only provide an initial overview of the new dataset of Lessmann and Seidel (2017) in the context of ASEAN regions. In the next subsections we summarize two methodologies that will help us better understand the dynamics of regional convergence and spatial dependence. Taken together, an analysis of economic convergence and spatial de-

[6] To control for the effect of some very rich regions (mainly from Brunei), one can evaluate the dynamics of the interquartile range (IQR), which is less sensitive to extreme observations. From this perspective, regional disparities appear to have increased over time.

pendence may prove useful for both designing and monitoring regional integration policies as one focuses on the time dimension of regional integration and the other focuses on the geographical location of regional clusters with high spatial dependence.

3.2 Measuring regional convergence

Following the classical convergence framework of Barro and Sala-i Martin (1991), the speed of regional convergence (β) can be estimated based on the following regression model:

$$\frac{1}{t}\, log\left(\frac{y_t}{y_0}\right) = \gamma - \frac{(1-e^{-\beta t})}{t}\, log\, y_0 + u_t, \tag{1}$$

where y_0 is the initial level of income, $(1/t)\, log\,(y_t/y_0)$ is the average growth rate between time 0 and time t, γ is a constant term, and u_t is a random disturbance that represents unexpected changes in technologies, institutions or preferences.

In addition to the speed of convergence (β), a second parameter of interest, can be computed as

$$half\text{-}life = \frac{log 2}{\beta}. \tag{2}$$

This second parameter, known as the "half-life" measure of convergence, measures the time that a representative economy would need to halve the distance between its initial position and its long-run equilibrium.

Despite the literature's emphasis on the measurement of beta convergence, it has also been acknowledged that beta convergence is not a sufficient condition for the reduction of regional inequality over time (Quah 1993; Sala-i Martin 1996; Young et al 2008). As such, a complementary notion of convergence has been suggested. The concept of sigma convergence directly describes the (average) dynamics of the cross-sectional dispersion. As such, sigma convergence implies that the distribution of income across economies is becoming more equitable over time. From a measurement standpoint, analyses of sigma convergence commonly estimate the standard deviation of the log of GDP per capita and evaluate it at multiple periods of time. When a systematic reduction in the standard deviation is observed, then a process of sigma convergence is taking place.

3.3 Measuring spatial dependence

An analysis of global spatial dependence aims to test the hypothesis of spatial randomness and the existence of an overall pattern of clustering. From a measurement standpoint, it is commonly based on the Moran's I statistic. In the context of a regional income analysis, this statistic describes the association of the income value at one location with the income values at neighboring locations (Anselin et al 2007; Anselin 1995). For any time period t, the global Moran's I statistic is defined as

$$I_t = \frac{N}{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \left[\frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij} \left(X_i - \bar{X}\right) \left(X_j - \bar{X}\right)}{\sum_{i=1}^{n} \left(X_i - \bar{X}\right)^2} \right], \tag{3}$$

where N is the number of regions under analysis, w_{ij} is an element of a spatial weights matrix (W) that defines the neighborhood structure between each pair of regions, X_i and X_j are the income values of regions i and j, respectively; and $\bar{X}$ is the average value of income.

When the Moran's I is statistically different from zero, then the null hypothesis of spatial randomness can be rejected. Intuitively similar to a standard correlation coefficient, the numerical value of the Moran's I statistic lies between plus and minus one. When its value is close to one, it indicates positive spatial autocorrelation. That is, evidence of an overall clustering pattern of similar values. On the other hand, when its value is close to minus one, it indicates negative spatial autocorrelation. That is, evidence of spatial dissimilarity, which at its limit it could be similar to a chessboard-like pattern where low values are surrounded by high values and vice versa.

An analysis of local spatial dependence aims to identify the location of spatial clusters and spatial outliers (Anselin et al 2007; Anselin 1995). From a measurement standpoint, it is commonly based on the breaking up of a global statistic of spatial dependence. In particular, for the case of the Moran's I statistic and in the context of a regional income evaluation, it potentially classifies regions into four groups. Regions with high income values surrounded by neighbors with high income values (that is, a high-high cluster). Regions with low income values surrounded by neighbors with low income values (that is, a low-low cluster). Regions with high income values surrounded by neighbors with low income values (that is, a high-low group). And regions with low income values surrounded by neighbors with high income values (that is, a low-high group). The first two groups (high-high and low-

low clusters) identify the location of spatial clusters (also known as hotspots and coldspots). The other two groups (high-low and low-high groups) identify the location of spatial outliers. For any time period t, a local Moran's statistic is defined for each region i as

$$I_{it} = \left(\frac{X_i - \bar{X}}{m_o} \right) \sum_{j=1}^{n} w_{ij} \left(X_j - \bar{X} \right) \text{ with } m_o = \sum_{i=1}^{n} \frac{\left(X_i - \bar{X} \right)^2}{n}, \tag{4}$$

where the notation follows that of the previously described global Moran's I.

4 Results

4.1 Luminosity intensity vs luminosity-based GDP: Which one is better?

There is a growing literature that uses luminosity intensity as a direct proxy for national and regional income (Alesina et al 2016; Henderson et al 2012; Mveyange 2018). However, compared to the national level, luminosity alone has less explanatory power at the regional level (Chen and Nordhaus 2011). Motivated by the relatively low explanatory power at the regional level, Lessmann and Seidel (2017) use additional indicators to compute a luminosity-based GDP per capita proxy. In addition to luminosity intensity, the econometric model to estimate luminosity-based GDP includes country-level GDP per capita, number of top and dark coded pixels of satellite scans at the regional level, number of regions within a country, overall size of a country, interaction between country size and number of regions, country-group fixed effects, country fixed effects, regional fixed effects, and satellite configuration fixed effects. Based on these variables and a sample of 5,258 regions from 81 countries, these authors are able to explain 76 percent (R^2 within) of the actual differences in GDP per capita across subnational regions. Compared to the initial 33 percent fit of luminosity alone, the model with additional variables predicts much more accurately the actual differences in GDP per capita across regions.

In this section, we re-evaluate the findings of Lessmann and Seidel (2017) in the context of the subnational regions of ASEAN. First, using a simple polled regression model, we evaluate the relationship between GDP per capita and luminosity intensity in those ASEAN regions where official data on re-

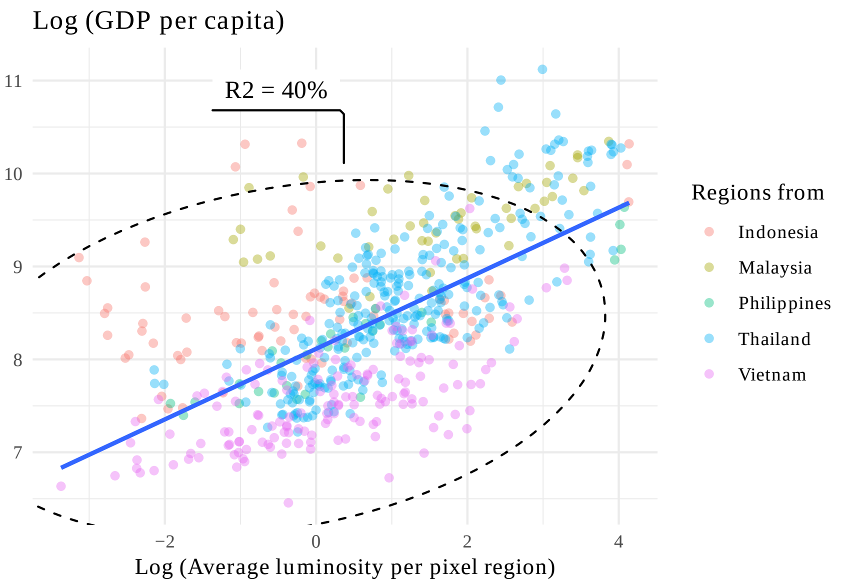


Fig. 2: Relationship between GDP per capita and luminosity intensity in a sample of ASEAN regions

Notes: Covering multiple time periods, observations constitute the first-level sub-national regions across five ASEAN countries. Luminosity data are from Lessmann and Seidel (2017) and regional GDP data are from Gennaioli et al (2013). This is an unbalanced panel dataset and its country-year coverage is as follows: Indonesia(1996, 2005, 2010), Malaysia (1995, 2000, 2005, 2010), Philippines(1992, 1997, 2006, 2010), Thailand(1995, 2000, 2005, 2010), Vietnam(1995, 2000, 2006, 2008).

gional GDP is available and comparable.[7] Results indicate that only 40 percent of regional GDP per capita differences are explained by luminosity intensity differences (see Figure 2).

Second, using the same econometric model and data, we evaluate the relationship between GDP per capita and luminosity-based GDP. This second variable, as previously explained, has been constructed by Lessmann and Seidel (2017) using luminosity intensity and additional control variables.[8] Results indicate that 59 percent of regional GDP per capita differences are explained by luminosity-based GDP differences (see Figure 3).

Overall, the results for the ASEAN sample are consistent with those reported by Lessmann and Seidel (2017) for the global sample. Compared to the initial 40 percent fit of luminosity alone, luminosity-based GDP predicts

[7] For this analysis, regional GDP data are from Gennaioli et al (2013).

[8] See Section 2.2.1 of Lessmann and Seidel (2017) for further details about the econometric specification and control variables.

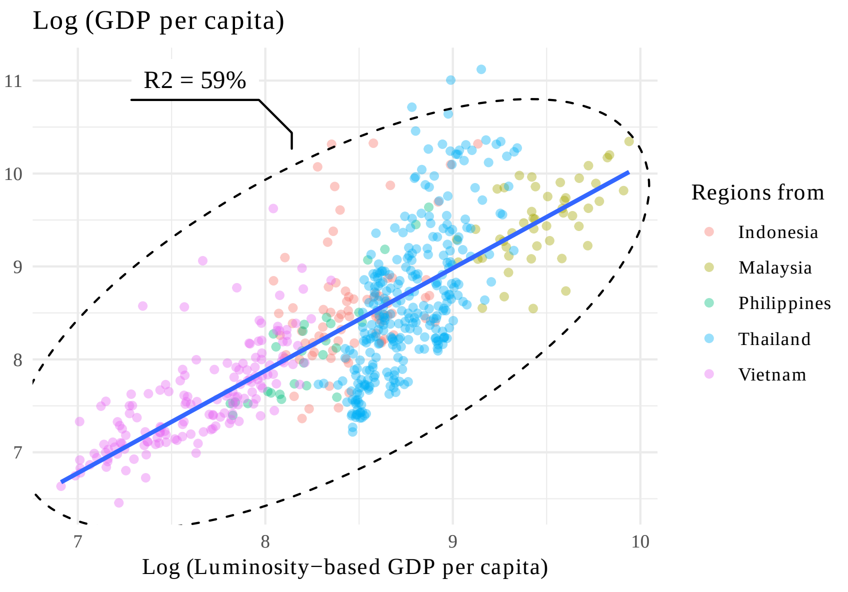


Fig. 3: Relationship between GDP per capita and luminosity-based GDP per capita in a sample of ASEAN regions

Notes: Covering multiple time periods, observations constitute the first-level sub-national regions across five ASEAN countries. Luminosity-based GDP data are from Lessmann and Seidel (2017) and observed GDP data are from Gennaioli et al (2013). This is an unbalanced panel dataset and its country-year coverage is as follows: Indonesia(1996, 2005, 2010), Malaysia (1995, 2000, 2005, 2010), Philippines(1992, 1997, 2006, 2010), Thailand(1995, 2000, 2005, 2010), Vietnam(1995, 2000, 2006, 2008).

much more accurately (59 percent fit) the actual differences in GDP per capita across ASEAN regions. Thus, in the following subsections, we use luminosity-based GDP per capita as the main variable for the analysis of regional convergence and spatial dependence.

4.2 Convergence across subnational regions in ASEAN

Figure 4 shows the results of sigma convergence for a balanced panel dataset of 274 ASEAN regions over the 1998-2012 period. Using two alternative indicators of dispersion, the standard deviation and the coefficient of variation, a similar pattern is observed: on average, across all ASEAN regions, disparities in luminosity-based GDP per capita have systematically declined over time. In 1998, for instance, the standard deviation was 0.82; by 2012 it decreased to 0.67. The convergence dynamics—at the ASEAN community level—show a smooth downward tendency for most of the entire period. Only in the 2008-

2012 sub-period, we can observe some fluctuations. A further investigation, beyond the scope of this paper, could evaluate to what extent regional disparities in ASEAN are affected by global shocks such as the 2008-2009 global financial crisis.

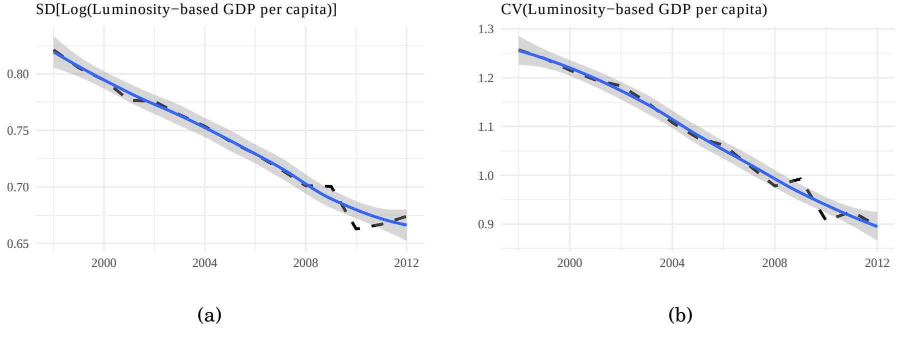


Fig. 4: Sigma convergence within the entire ASEAN community

Notes: The dashed line is an observed measure of regional dispersion. SD stands for standard deviation and CV stands for coefficient of variation. The solid line and its associated confidence interval indicate a predicted measure of regional dispersion, which has been estimated using a local nonparametric regression. Each indicator is computed for every year, using a panel dataset of 274 first-level sub-national ASEAN regions. Singapore is not included in the sample.

The convergence dynamics at the community level appear to be hiding weaker patterns of convergence within countries. The first two columns of Table 2 report standard deviations of luminosity-based GDP per capita for each of the nine ASEAN countries in 1998 and 2012. Statistical significance is evaluated based on a dispersion ratio test, where the null hypothesis is that the value of the ratio of the two standard deviations is equal to one. The most striking finding is that, at the ASEAN community level, there is a statistically significant convergence (see the dispersion ratio: 1.22***). However, within each country, convergence is not statistically significant.

To confirm this weak pattern of convergence within countries, statistical significance is re-evaluated based on the slope coefficient of a linear regression between the standard deviation and a time index. From this analysis, only Brunei, Indonesia, Vietnam, and Malaysia show a statistically significant reduction in inequality. In contrast, the decrease in inequality in Thailand, Philippines, Laos, and Cambodia is not statistically significant. Of particular interest is the case of Myanmar, as it is the only ASEAN country that shows a statistically significant divergence. Taken together, these findings indicate

Table 2: Sigma convergence within the countries of ASEAN

Country	Dispersion 1998	Dispersion 2012	Ratio 1998/2012	Slope Coefficient
Brunei	0.1990	0.1746	1.14	-0.0020***
Thailand	0.1373	0.1258	1.09	-0.0007
Indonesia	0.1985	0.1852	1.07	-0.0010***
Philippines	0.1727	0.1662	1.04	-0.0008
Vietnam	0.1286	0.1249	1.03	-0.0009***
Malaysia	0.1550	0.1522	1.02	-0.0005*
Laos	0.1422	0.1399	1.02	-0.0001
Cambodia	0.1758	0.1783	0.99	-0.0011
Myanmar	0.1551	0.1633	0.95	+0.0010*
Total ASEAN	0.8212	0.6741	1.22***	-0.0110***

Note: The dispersion of (log) luminosity-based GDP per capita has been measured using the standard deviation. Statistical significance is evaluated based on a dispersion ratio test, where the null hypothesis is that the value of the ratio of the 1998-2012 standard deviations is unity. The slope coefficient is from a linear regression between the standard deviation and time index. *, **, *** indicate signicance at the 10%, 5%, 1% level respectively.

that masked behind the overall (average) convergence pattern of the ASEAN community, there is still a high degree of regional heterogeneity within countries.

Figure 5 further illustrates the dynamics of regional convergence within each country. Two new findings emerge from this figure. First, the dynamics of convergence show a highly non-linear behaviour. In particular, countries such as Laos, Myanmar, and the Philippines exhibit waves of convergence followed by waves of divergence, and vice versa. Second, with the exception of Myanmar, a reduction in regional inequality is taking place since the mid 2000s.

In Figure 6 the relationship between the (luminosity-based) growth rate of GDP per capita and the initial GDP per capita is shown for the 274 ASEAN regions. On average, it appears that the poorest regions are growing faster that the richest ones. In order to evaluate the statistical significance of this relationship, linear regressions are performed both at the entire ASEAN community level and within each country. The speed of regional convergence is recovered from the slope of the regression described in Equation 1 and the "half-life" time of convergence (in years) is computed using Equation 2. All these results are reported in Table 3.

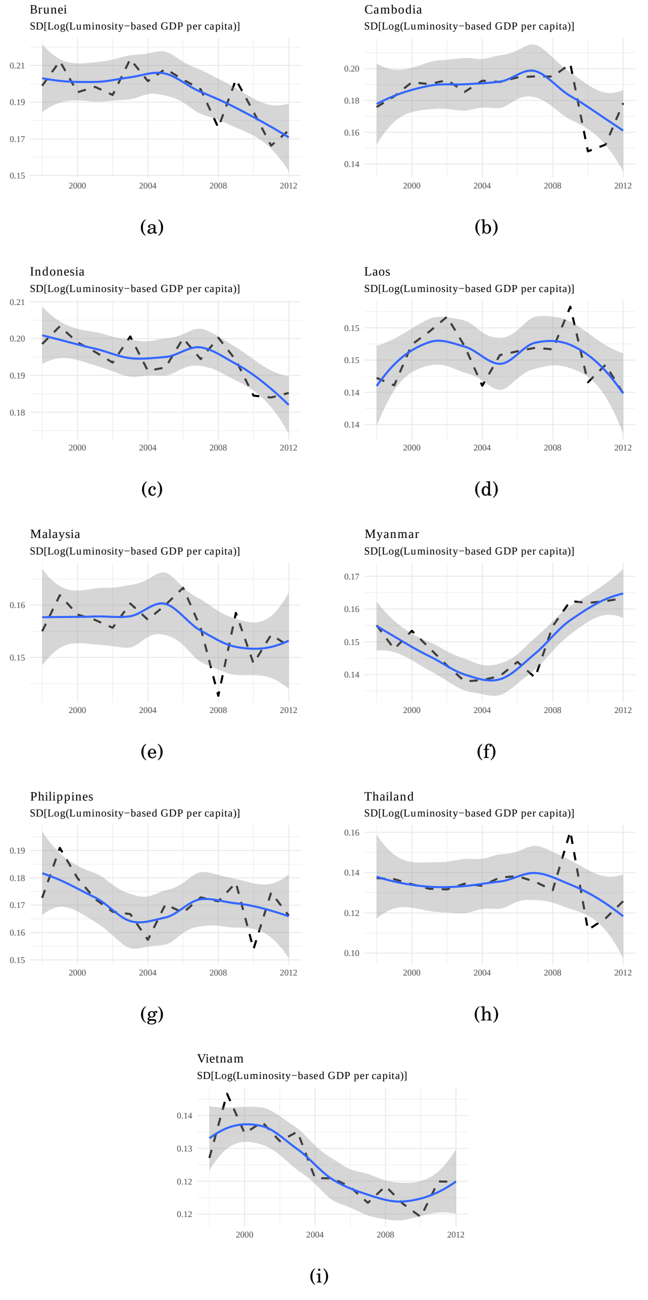


Fig. 5: Sigma convergence within ASEAN countries

Notes:The dashed line is an observed measure of regional dispersion. SD stands for standard deviation. The solid line and its associated confidence interval indicate a predicted measure of regional dispersion, which has been estimated using a local nonparametric regression.

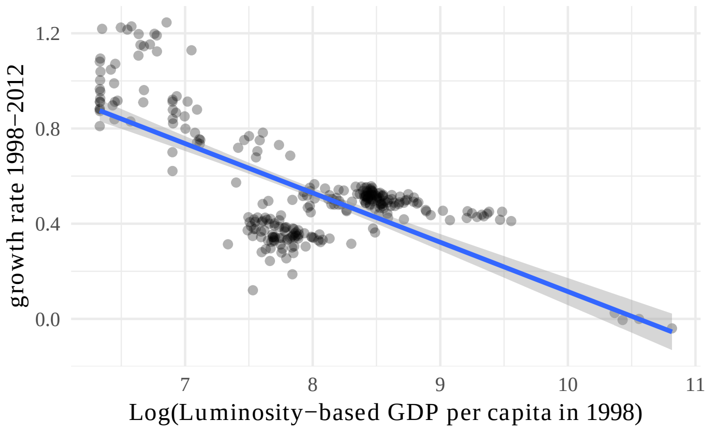


Fig. 6: Beta convergence within the entire ASEAN community

Notes: The solid line and its associated confidence interval indicate the fit of a linear regression.

For all ASEAN regions (last row in Table 3), it can be concluded that there is beta convergence, with a highly significant coefficient and a half-life time of convergence of 41.8 years. Interestingly, the speed of convergence is around 2%, which is commonly reported in the literature of regional convergence in the US, Japan, and Europe (Barro and Sala-i Martin 1991).

Table 3: Beta convergence within the countries of ASEAN

Country	Beta coefficient	Speed of convergence	Half-life(years)
Brunei	-0.12*	0.009	73.2
Thailand	-0.12***	0.009	79.3
Indonesia	-0.08***	0.006	120.0
Philippines	-0.10**	0.007	92.6
Vietnam	-0.07	0.005	132.5
Malaysia	-0.02	0.002	420.9
Laos	-0.20	0.016	42.6
Cambodia	-0.13	0.010	68.1
Myanmar	0.00	-	-
Total ASEAN	-0.21***	0.017	41.8

Note: The beta coefficient is the coefficient of a linear regression given by equation 1, the speed of convergence can be recovered from the beta coefficient and the half-life is calculated using equation 2. *, **, *** indicate signicance at the 10%, 5%, 1% level, respectively.

The patterns of beta convergence within countries are much weaker and most of them are not statistically significant. For example, countries such as

Brunei, Thailand, Indonesia and Philippines present significant coefficients and half-lives that range between 79 and 120 years. The speeds of convergence associated with those coefficients are around half of the one reported for the entire ASEAN community. For the other countries, they either show non-significant coefficients or very slow speeds of convergence.

One more outstanding finding can be drawn from the results of Table 3. It seems that the richest ASEAN members are experiencing within-country convergence, while most of the poorest members show no signs of (statistically significant) within-country convergence. Nevertheless, Malaysia is an exception to this pattern. It is the only relatively rich country in ASEAN that shows no signs of significant (within-country) regional convergence. If anything, its very slow speed of convergence would imply that even after 421 years, the average Malaysian region would only close 50 percent of its luminosity-based GDP per capita gap.

Although previous convergence studies in ASEAN have focused on country-level data, the regional-level results of this paper may help clarify some inclusive debates. Consistent with the results of Ismail (2008) and Solarin et al (2014), in this paper we find evidence of convergence when we evaluate all subnational regions independently of their country of origin. Within some countries (Cambodia, Laos, Malaysia, and Vietnam), however, beta convergence is not statically significant. Moreover, the subnational regions of Myanmar show clear sings of sigma divergence. Thus, these within-country results appear more consistent with the findings of Park (2000) and Alavi and Ramadan (2008) who report no evidence of income convergence.

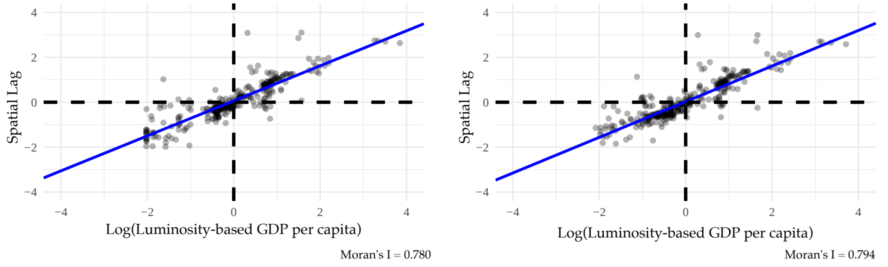
4.3 Spatial dependence across subnational regions in ASEAN

In order to explore spatial patterns, a shapefile of ASEAN regions is used[9]. Moreover, in order to calculate spatial autocorrelation statistics, a spatial weight matrix is also needed. To create this this matrix, the queen contiguity criteria is standard in the literature. However, in the sample of ASEAN regions many island-regions are included and in some instances the distance between them

[9] At this point, it is worth mentioning that the luminosity-based GDP per capita for Vietnam is given at the economic area level (8 areas). However, such areas are not formally the first administrative level. The first administrative level for Vietnam includes 58 provinces and 5 municipalities and for this reason the shapefile used in this paper includes provinces and municipalities. In order to use this type of shapefile, it is assumed that the data at the economic area level can also be assigned to each province that is within that economic area.

can be relatively large. For example, using a distance band, the minimum distance for all regions in ASEAN to have at least one neighbor was found to be 697km. This band seems appropriate for an archipelago like Indonesia, however, this distance band can leave some regions in Thailand or Cambodia with as many as 150 neighbors.

In order to assign neighbors to all locations it is preferred to consider a set number for each region, a criteria which is known as the k-nearest neighbors approach. When considering the sub-sample of all regions in ASEAN that have at least one land bordering region, the mean of the number of neighbors is 4.52. Rounding up this number to 5, it seems plausible to use the 5 nearest neighbours as the criteria for computing the spatial weights matrix.



(a) 1998 (b) 2012

Fig. 7: Global Moran's I and scatter plots

Using equation 3, the value for the global Moran's I is computed for each year of the sample period. In Figure 7 the Moran's I scatter plots are shown for the initial and final year of the sample. Overall, for all years, this statistic is highly significant and within a small range: $0.780 \leq I \leq 0.794$. In addition, global spatial autocorrelation shows an increasing tendency from 2008 (Figure 8). In this graph, the Moran's statistic for the luminosity-based GDP per capita without log is also plotted. For this variable, the upward tendency in spatial dependency is more evident and it is present since 1998. Positive and significant values of the Moran's I indicate that, on average, regions tend to be surrounded by neighbors with similar values. The existence of spatial clustering suggests that it is possible to perform spatial regressions when evaluating beta convergence, this type of analysis is left for future research.

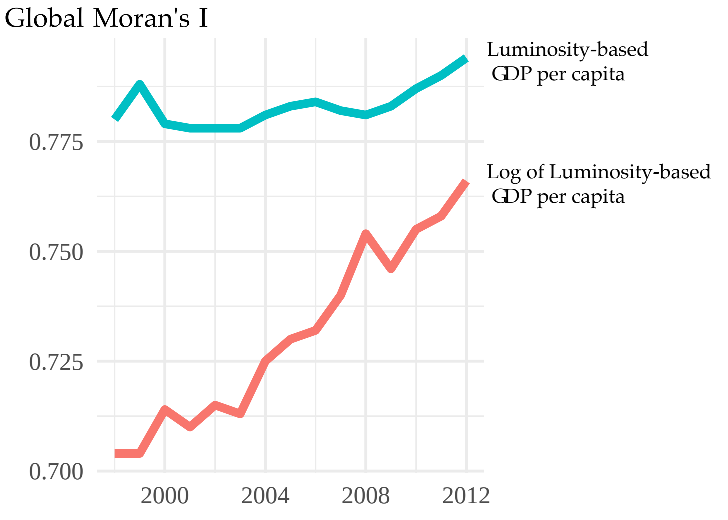


Fig. 8: Global Moran's I over time

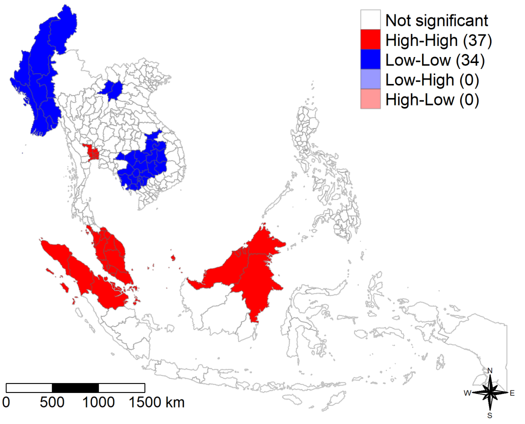
Notes: GDP per capita refers to the the luminosity-based GDP per capita. All global Moran's I statistics are significant with a (pseudo) p-value less than 0.01.

In terms of the local analysis of spatial dependence, Figure 9 shows the location of spatial clusters (hotspots and coldspots) for the years 1998 and 2012. Regions in the choropleth maps are considered members of a cluster if the p-value of the local Moran's I is lower than 0.01 [10]. On average, it seems that panels (a) and (b) are relatively similar, which means that there is a relatively high spatial persistence in terms of cluster size and membership.

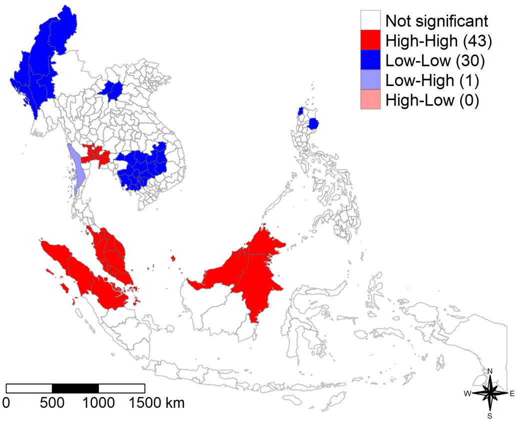
Overall, low GDP clusters (coldspots) are located in Myanmar and Cambodia. In 1998, 9 out of the 14 regions of Myanmar belonged to a low GDP cluster, while 20 out of the 24 regions of Cambodia belonged to a low GDP cluster. Nevertheless, some regions escaped and some others joined these clusters. Over time the size of the low GDP clusters decreased from 34 to 30 regions. In the one hand, the six regions that are not longer part of the low GDP cluster in 2012 include three regions from Myanmar, two regions from southern Laos and one region from the coastal area of Cambodia. On the other hand, the two regions that became part of this type of cluster are located in the north of the Philippines.

High GDP clusters include regions from Thailand, Malaysia, Brunei and Indonesia. In the year 2012, 6 more regions joined these clusters. Interestingly,

[10] The significance maps are reported in Appendix A.



(a) Cluster map for 1998



(b) Cluster map for 2012

Fig. 9: Local Moran's I for Log(Luminosity-based GDP per capita)

all these newly joint regions are located in central Thailand. As this cluster grew in size, it also got closer to the boarder of south Myanmar. Thus, a new high-low GDP group was formed from a single region in that country.

The part of ASEAN near the equator line, where Brunei, Singapore and Malaysia are located, includes most of the regions in the high GDP cluster. All regions of Malaysia and Brunei are included, together with four regions in southern Thailand and five Indonesian regions. All these regions were part of the high GDP clusters both in 1998 and 2012.

Finally, as previously mentioned, clusters are not necessarily located within countries. Some clusters are formed on both sides of national boundaries. In 1998 and 2012, low-GDP clusters were composed by Cambodian and Lao regions; and the most proximate neighbors of this cluster include regions from Vietnam and Thailand.

Some of the high GDP clusters also spread beyond national boundaries. The regions in southern Thailand form a cluster with the Malaysian regions in the Malay Peninsula. In addition, in the island of Borneo, all regions of Brunei, two of Malaysia, and one region of Indonesia form another high GDP cluster.

5 Policy implications

Taken together, the previous results provide a new and more disaggregated perspective of the integration process of the ASEAN community. As suggested by the experience of other economic communities (for instance, the European Union), achieving economic integration goes hand in hand with the reduction of regional disparities across the members of the community. In addition, reducing regional disparities is central for achieving sustainable development. The importance of reducing inequality among and within countries is clearly stated in the declaration of the Sustainable Development Goals.

More specifically, the results of this paper could inform the design and monitoring of regional integration policies across the members of the ASEAN community in two fronts. First, in Figure 9, three persistent clusters of low income are identified. The low economic growth of the north-western regions of ASEAN should be a major concern for the integration and sustainability of the entire ASEAN community. Given the spatial configuration of the clusters, targeted policies at the cluster level policies may prove useful. In particular, investment spillovers from the subnational regions of Thailand (the fourth richest country in ASEAN) could play a role in enabling the development of neighboring lagging regions.[11]

Second, continuous monitoring and evaluation of the scope by which inequality has been reduced both within and among countries is crucial to for the sustainable development of the ASEAN community. The importance of this task has already been singled out by the international community.

[11] There is an expanding high-income spatial cluster in Thailand that has crossed the Myanmar border. In the near future, this spatial cluster could grow beyond the border with Cambodia

The goal of inequality reduction became the 10th goal of the Sustainable Development Goals (SDGs) adopted by all United Nations member states. A luminosity-based GDP per capita database appears to be a powerful tool for measuring the evolution of regional inequality. Currently, the database created by Lessmann and Seidel (2017) provides regional income data up to 2012. Extending the database for recent years, improving the specification of the prediction model, and including newly reported regional GDP may help increase its accuracy. A better prediction of regional GDP may help both researchers and policymakers alike to evaluate progress in inequality reduction across countries as well as subnational regions.

6 Concluding remarks

A large number of studies have evaluated income disparities and convergence patterns among ASEAN countries. Results, however, appear mixed and inconclusive as they largely depend on time frame and sample coverage. Given that the ASEAN community is conformed by only ten countries, many previous studies are largely constrained by a small sample size problem. This constrain is particularly binding for the analyses of economic convergence and spatial dependence, which typically require a larger sample size to correctly infer the evolution of economic disparities over time and space.

In an attempt to increase the sample size and infer the evolution of economic disparities over time and space, we use the new regional income dataset of Lessmann and Seidel (2017) that has been constructed using satellite night-time light data. This new dataset covers 274 subnational regions of the ASEAN community over the 1998-2012 period. Our main results are threefold. First, in the context of ASEAN related studies, the dataset of Lessmann and Seidel (2017) is useful in the sense that almost 60 percent of the differences in (official) GDP per capita can be predicted by a luminosity-based measure of GDP per capita. Next, the regional dynamics of this predicted GDP per capita measure suggest a pattern of regional convergence for the entire ASEAN sample. However, regional inequality has not significantly decreased within the majority of the individual countries of ASEAN. Third, there is an increasing degree of spatial dependence over time and some stable spatial clusters (hotspots and coldspots) are identified across multiple national boundaries.

As this is the first study that evaluates spatio-temporal dynamics using luminosity data across subnational regions in ASEAN, we only provided an exploratory perspective using a classical convergence framework and a standard spatial dependence analysis. Although these two methodologies are complementary from a time-space analysis point of view, we did not fully integrate them in this paper. We leave this task for further research. In particular, from a spatial econometric perspective, one could evaluate to what extend spatial dependence accelerates or decelerates the speed of convergence.[12] In addition, from a non-parametric distributional perspective, one could evaluate how spatial dependence affects the regional income distribution and its evolution.[13]

[12] See Rey and Montouri (1999) for one the seminal contributions in this line of research. More recent surveys are presented in Abreu et al (2005) and Rey and Le-Gallo (2009).

[13] See Quah (1993) and Rey (2001) for two seminal contributions in this line of research. More recent surveys are presented in Rey (2015) and Rey (2019).

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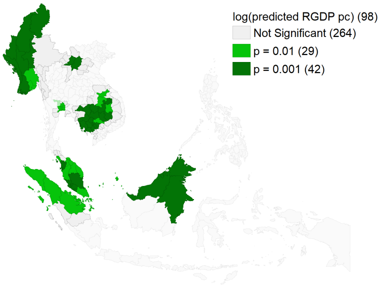
Appendix

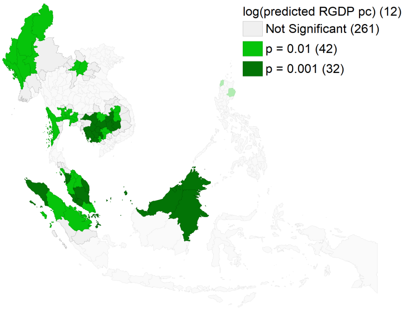
A Significance map of the local Moran's I

Fig. 10: Significance map for the local Moran's I for log(luminosity based regional GDP pc)

(a) Significance map for 1998



(b) Significance map for 2012



B List of ASEAN regions and luminosity-based GDP per capita in selected years

Table 4: Brunei's first-level subnational regions

	Region	Year1998	Year2005	Year2012
1	Temburong	31781.15	31156.76	32577.63
2	Belait	33829.60	34450.44	33667.58
3	Tutong	38476.07	38117.24	38463.04
4	Brunei and Muara	49808.02	50506.77	47855.34

Table 5: Cambodia's first-level subnational regions

	Region	Year1998	Year2005	Year2012
1	Môndól Kiri	561.93	905.92	1262.94
2	Stœng Trêng	562.22	906.39	1346.13
3	Preah Vihéar	561.86	905.80	1355.45
4	Pouthisat	562.15	906.27	1359.99
5	Kâmpóng Thum	562.08	906.15	1399.25
6	Kâmpóng Chhnang	564.07	909.37	1403.71
7	Otdar Mean Chey	564.13	957.98	1424.54
8	Kaôh Kong	630.61	994.87	1458.73
9	Prey Vêng	564.37	909.86	1467.89
10	Krâchéh	562.24	906.41	1476.75
11	Batdâmbâng	621.49	1194.68	1524.35
12	Kâmpóng Spœ	563.54	908.53	1536.03
13	Kâmpóng Cham	632.41	1092.69	1573.94
14	Takêv	565.10	1038.88	1596.73
15	Bântéay Méanchey	646.17	1194.31	1616.53
16	Krong Pailin	714.76	1091.25	1638.70
17	Rôtânôkiri	562.28	906.47	1657.10
18	Kâmpôt	564.40	955.27	1685.61
19	Siemréab	628.78	1203.06	1691.88
20	Svay Rieng	612.98	1133.93	1747.21
21	Kep	572.35	922.72	1936.53
22	Krong Preah Sihanouk	790.42	1385.20	1963.50
23	Kândal	794.55	1336.04	2077.80
24	Phnom Penh	1204.38	1974.40	2901.71

Table 6: Philippines's first-level subnational regions

	Region	Year1998	Year2005	Year2012
1	Apayao	1534.53	1804.96	2099.36
2	Mountain Province	1866.14	1835.88	2104.62
3	Aurora	1791.06	2271.67	2598.41
4	Abra	1863.82	2242.26	2639.87

5	Romblon	1998.71	2300.35	2645.58
6	Ifugao	1838.67	2127.23	2714.16
7	Occidental Mindoro	2131.92	2488.83	2719.24
8	Kalinga	1819.88	2124.88	2732.25
9	Eastern Samar	1882.65	2215.97	2745.45
10	Northern Samar	1801.06	2203.30	2760.90
11	Sulu	2064.36	2293.83	2766.62
12	Tawi-Tawi	1906.45	2314.85	2780.69
13	Dinagat Islands	1989.36	2049.36	2804.32
14	Batanes	1899.09	2311.04	2855.77
15	Agusan del Sur	1882.66	2192.02	2859.93
16	Davao Oriental	1989.37	2333.11	2871.16
17	Palawan	2143.94	2444.68	2883.20
18	Quirino	1636.30	1988.69	2901.75
19	Samar	2100.39	2378.04	2920.11
20	Catanduanes	2040.81	2452.66	2958.27
21	Masbate	1935.61	2324.65	2963.86
22	North Cotabato	2156.87	2497.22	2981.30
23	Camiguin	2002.67	2233.76	3007.68
24	Cagayan	2016.40	2399.19	3043.73
25	Sarangani	2202.13	2464.93	3052.97
26	Lanao del Sur	2199.68	2508.83	3064.10
27	Basilan	2543.09	2576.77	3067.41
28	Compostela Valley	2177.94	2481.97	3070.04
29	Shariff Kabunsuan	2334.15	2568.32	3083.40
30	Sultan Kudarat	2185.78	2440.75	3083.85
31	Nueva Vizcaya	2205.24	2543.38	3102.29
32	Oriental Mindoro	2175.73	2645.29	3102.30
33	Marinduque	2424.48	2627.61	3126.71
34	Zamboanga del Norte	2221.03	2503.72	3135.86
35	Antique	2055.44	2372.74	3144.87
36	Maguindanao	2353.11	2580.30	3159.38
37	Zamboanga Sibugay	2083.71	2589.38	3161.67
38	Capiz	2316.81	2627.69	3166.37
39	Surigao del Sur	2123.87	2349.39	3168.41
40	Bukidnon	2300.54	2740.97	3233.76
41	Southern Leyte	2139.94	2611.12	3257.64
42	Biliran	2014.09	2523.61	3264.06
43	Isabela	2212.37	2551.15	3273.12
44	Camarines Norte	2335.56	2672.83	3279.85
45	Sorsogon	2210.70	2716.69	3302.04
46	Aklan	2290.08	2740.89	3369.74
47	Misamis Occidental	2562.48	2797.99	3377.72
48	Quezon	2437.35	2812.67	3393.83
49	Lanao del Norte	2536.93	2820.02	3424.58
50	Agusan del Norte	2452.42	2807.85	3430.76

51	Surigao del Norte	2395.00	2720.33	3457.46
52	Siquijor	2106.73	2659.78	3458.01
53	Guimaras	2295.12	2653.33	3474.06
54	Ilocos Norte	2387.02	2872.94	3491.69
55	Zamboanga del Sur	2580.45	2945.40	3501.33
56	Camarines Sur	2500.87	2949.87	3513.32
57	Ilocos Sur	2400.95	2861.84	3524.74
58	Negros Oriental	2420.94	2768.12	3559.17
59	Leyte	2529.27	2935.91	3571.29
60	Bohol	2326.00	2750.19	3593.35
61	Albay	2558.35	2990.59	3631.16
62	Zambales	2588.16	2979.99	3641.21
63	Davao del Norte	2587.49	3027.12	3705.09
64	Negros Occidental	2615.03	3041.75	3708.78
65	Iloilo	2551.20	3012.81	3730.41
66	La Union	2663.22	3087.09	3734.59
67	Benguet	2573.85	3096.20	3753.66
68	Nueva Ecija	2652.12	3105.51	3754.64
69	South Cotabato	2615.47	3022.02	3764.15
70	Misamis Oriental	2678.83	3102.01	3821.00
71	Davao del Sur	2821.64	3151.07	3824.85
72	Pangasinan	2663.96	3170.95	3865.51
73	Tarlac	2793.60	3279.57	4003.01
74	Cebu	2949.98	3375.07	4165.35
75	Bataan	2971.44	3409.55	4183.75
76	Batangas	3004.36	3470.45	4225.64
77	Bulacan	3118.72	3546.39	4336.25
78	Laguna	3169.34	3624.10	4375.92
79	Pampanga	3144.80	3692.82	4484.43
80	Rizal	3223.49	3679.68	4494.27
81	Cavite	3404.17	3845.53	4770.89
82	Metropolitan Manila	4034.92	4727.35	5532.15

Table 7: Thailand's first-level subnational regions

	Region	Year1998	Year2005	Year2012
1	Mae Hong Son	3805.84	4828.54	6527.14
2	Phatthalung (Songkhla Lake)	4861.62	5941.77	6989.08
3	Songkhla (Songkhla Lake)	4784.57	5637.12	6993.59
4	Nan	4224.54	5327.64	7139.73
5	Tak	4175.13	5641.72	7277.51
6	Amnat Charoen	4316.33	5815.81	7293.45
7	Mukdahan	4478.41	5975.93	7485.51
8	Ubon Ratchathani	4463.90	5816.68	7494.47

9	Yasothon	4568.93	6022.24	7538.28
10	Si Sa Ket	4521.63	5814.43	7568.99
11	Loei	4422.66	5744.91	7571.87
12	Sakon Nakhon	4525.46	5980.40	7575.77
13	Uthai Thani	4365.79	5911.19	7610.34
14	Surin	4587.39	5853.29	7623.64
15	Nakhon Phanom	4530.92	5976.40	7625.80
16	Nong Khai	4585.13	5998.80	7692.45
17	Ranong	4857.04	6154.03	7720.35
18	Roi Et	4699.64	6148.72	7758.43
19	Trat	5013.27	6358.27	7789.09
20	Phetchabun	4557.32	6044.39	7796.77
21	Chaiyaphum	4495.19	5957.64	7799.88
22	Uttaradit	4598.00	5958.33	7820.81
23	Buri Ram	4663.57	6008.62	7825.46
24	Kanchanaburi	4778.83	6181.94	7833.49
25	Phayao	4750.31	5928.01	7850.71
26	Sa Kaeo	4549.98	6114.14	7915.25
27	Phrae	4732.15	6095.92	7959.45
28	Kamphaeng Phet	4763.31	6100.98	8028.98
29	Chanthaburi	5046.75	6464.72	8042.00
30	Lampang	4793.80	6118.09	8046.35
31	Phitsanulok	4686.24	6329.01	8048.28
32	Phichit	4694.64	6444.58	8104.53
33	Kalasin	4755.46	6434.93	8131.87
34	Yala	4779.10	6464.86	8133.25
35	Maha Sarakham	4745.31	6305.40	8136.33
36	Chiang Mai	4939.17	6353.52	8158.51
37	Chiang Rai	4919.22	6198.85	8179.76
38	Surat Thani	5063.52	6575.45	8197.73
39	Nakhon Sawan	4880.30	6437.65	8203.14
40	Phangnga	5091.71	6411.42	8228.45
41	Nong Bua Lam Phu	4713.92	5851.07	8231.98
42	Trang	5382.40	6775.48	8236.04
43	Sukhothai	4756.93	6268.57	8250.15
44	Udon Thani	4932.66	6355.14	8250.82
45	Lamphun	5041.06	6456.60	8260.09
46	Krabi	5203.15	6560.35	8280.81
47	Phatthalung	5108.12	6555.56	8291.08
48	Chumphon	5162.44	6528.29	8300.20
49	Nakhon Si Thammarat	5354.10	6647.94	8335.83
50	Nakhon Ratchasima	5030.26	6469.36	8358.61
51	Satun	5175.38	6589.29	8402.01
52	Narathiwat	4986.95	6766.10	8450.23
53	Chai Nat	5054.23	6767.33	8587.08
54	Prachuap Khiri Khan	5242.69	6724.48	8603.11

55	Lop Buri	5153.95	6755.31	8633.32
56	Khon Kaen	5163.96	6707.38	8661.49
57	Phetchaburi	5175.48	6691.44	8723.25
58	Prachin Buri	5357.05	6892.51	8731.14
59	Nakhon Nayok	5498.74	7003.64	8830.97
60	Songkhla	5408.11	7067.74	8917.84
61	Chachoengsao	5674.54	7198.33	9118.25
62	Ratchaburi	5544.03	7126.46	9172.77
63	Suphan Buri	5637.88	7250.53	9186.04
64	Pattani	5538.48	7369.45	9319.65
65	Sing Buri	5854.53	7517.40	9484.88
66	Saraburi	5890.44	7591.21	9609.91
67	Ang Thong	5910.64	7560.10	9878.12
68	Rayong	6092.43	7927.20	9923.43
69	Chon Buri	6170.06	8150.87	10146.65
70	Samut Songkhram	6252.78	8026.24	10314.81
71	Phra Nakhon Si Ayutthaya	6304.85	8124.62	10647.74
72	Nakhon Pathom	6568.42	8444.34	10745.96
73	Samut Sakhon	6752.33	8752.10	10961.76
74	Phuket	6590.71	8805.58	10974.58
75	Pathum Thani	6824.99	9078.50	11135.59
76	Samut Prakan	7260.97	9383.62	11410.30
77	Nonthaburi	7227.78	9422.72	11421.80
78	Bangkok Metropolis	7519.36	9777.61	11627.13

Table 8: Malaysia’s first-level subnational regions

	Region	Year1998	Year2005	Year2012
1	Sarawak	8271.08	10563.62	13027.82
2	Sabah	8740.88	10935.36	13234.17
3	Pahang	9972.73	12433.90	15239.78
4	Kelantan	10032.23	12635.10	15771.57
5	Trengganu	10391.32	13207.87	16194.94
6	Perak	10806.22	13375.54	16581.51
7	Kedah	11216.12	14236.20	17375.78
8	Johor	11396.97	14473.59	17537.21
9	Negeri Sembilan	11707.36	14717.37	18219.18
10	Perlis	11881.25	15495.87	18638.13
11	Selangor	12942.83	16526.82	19625.26
12	Melaka	13154.77	16986.23	20635.79
13	Pulau Pinang	14129.85	17816.05	21311.29

Data source: Lessmann and Seidel (2017)

Table 9: Indonesia's first-level subnational regions

	Region	Year1998	Year2005	Year2012
1	Papua	2542.28	3065.03	4191.55
2	Kalimantan Barat	2869.15	3519.10	4579.40
3	Irian Jaya Barat	2936.65	3512.28	4595.46
4	Kalimantan Tengah	2760.89	3364.52	4627.02
5	Maluku	2916.60	3654.50	4691.82
6	Sulawesi Barat	2775.64	3512.71	4731.63
7	Maluku Utara	2852.12	3397.18	4787.67
8	Sulawesi Tengah	2920.19	3553.91	4992.37
9	Nusa Tenggara Timur	3027.52	3694.43	5021.83
10	Sulawesi Tenggara	2914.50	3743.04	5056.88
11	Bengkulu	3020.01	3744.61	5319.42
12	Kalimantan Timur	3366.64	4072.21	5572.24
13	Gorontalo	3450.65	4169.95	5584.54
14	Bangka-Belitung	3284.31	4092.65	5681.25
15	Aceh	3531.69	4202.30	5707.18
16	Sumatera Barat	3400.46	4120.21	5717.78
17	Jambi	3475.00	4321.01	5747.43
18	Sulawesi Selatan	3546.36	4263.37	5818.49
19	Riau	3649.86	4237.73	5897.33
20	Kalimantan Selatan	3588.44	4365.26	5965.32
21	Nusa Tenggara Barat	3667.22	4481.61	6021.63
22	Sulawesi Utara	3731.54	4468.33	6036.84
23	Sumatera Selatan	3890.59	4505.59	6117.61
24	Sumatera Utara	3883.37	4553.05	6130.59
25	Lampung	3651.54	4536.77	6279.55
26	Kepulauan Riau	4054.25	4887.86	6634.45
27	Jawa Timur	4512.65	5462.20	7344.51
28	Jawa Tengah	4516.64	5478.17	7345.08
29	Bali	4470.32	5456.94	7349.22
30	Banten	4669.23	5508.07	7518.65
31	Jawa Barat	4668.49	5569.14	7550.18
32	Yogyakarta	4604.55	5751.49	7661.79
33	Jakarta Raya	6094.71	7316.21	9260.99

Table 10: Vietnan's first-level subnational regions

	Region	Year1998	Year2005	Year2012
1	Northwest	1662.76	2475.43	3412.29
2	Northeast	1911.57	2783.79	3768.10
3	Cental Highlands	1810.45	2648.74	3901.57
4	North Central	1933.11	2829.89	3911.50
5	South Central Coast	1969.00	2937.22	4170.53
6	Mekong River Delta	2017.88	3105.45	4412.55
7	Southest	2289.04	3403.46	4753.49
8	Red River Delta	2500.82	3599.53	4965.59

Table 11: Laos's first-level subnational regions

	Region	Year1998	Year2005	Year2012
1	Phôngsali	993.61	1356.01	1849.43
2	Houaphan	993.16	1355.41	2000.68
3	Oudômxai	998.03	1392.72	2269.61
4	Louang Namtha	995.46	1358.55	2306.40
5	Xékong	996.22	1392.71	2398.84
6	Saravan	1021.68	1358.50	2429.71
7	Louangphrabang	1099.79	1589.42	2445.71
8	Xaignabouri	993.62	1383.50	2475.85
9	Xiangkhoang	994.47	1455.62	2498.28
10	Bolikhamxai	1203.97	1521.00	2527.64
11	Bokeo	1092.80	1583.32	2559.10
12	Khammouan	1230.65	1702.83	2567.36
13	Savannakhét	1185.33	1733.47	2590.42
14	Champasak	1226.12	1690.56	2608.72
15	Xaisômboun	1026.85	1409.54	2617.42
16	Vientiane	1236.18	1693.84	2621.37
17	Attapu	1118.14	1417.17	2786.49
18	Vientiane	1743.23	2421.65	3695.71

Data source: Lessmann and Seidel (2017).