SSE RIGA

Bachelor Thesis

A View from Outer Space: Nighttime Light Intensity and Economic Activity in the Baltic municipalities

Authors:

Andrejs Migunovs
Romāns Vereteņņikovs

Supervisor:

Oļegs Krasnopjorovs

April 2020

Riga

COPYRIGHT DECLARATION

Names of the authors in full: Andrejs Migunovs, Romāns Vereteņņikovs

Title of the Thesis: A View from Outer Space: Nighttime Light Intensity and Economic Activity in the Baltic Municipalities

We hereby certify that the above-named thesis is entirely the work of the persons named below, and that all materials, sources and data used in the thesis have been duly referenced. This thesis – in its entirety or in any part thereof – has never been submitted to any other degree commission or published.

In accordance with Section 1 of the Copyright Law of Latvia, the persons named below are the authors of this thesis.

The authors hereby agree that SSE Riga may deposit one copy of this thesis in the SSE Riga Library. The authors grant SSE Riga the exclusive right, without royalty nor limitation, to publish this thesis in whole or in part in any publication of SSE Riga in any form for two calendar years following the year of graduation of the authors. We assert our right to be identified as the authors of this thesis whenever it is reproduced in full or in part.

Signed

Migunovs

/Andrejs Migunovs/ /Romāns Vereteņņikovs/

Date

5th April 2020

ACKNOWLEDGEMENT

We would like to acknowledge the contribution of our supervisor Oļegs Krasnopjorovs, Chief Economist of the Macroeconomic Analysis Division, Monetary Policy Department of Bank of Latvia, who very responsive and supportive during the whole working process and giving valuable feedback. Oļegs professionally helped us develop the ideas of the paper, as well as improve every part of the research.

Additionally, we would like to thank the faculty of the Stockholm School of Economics in Riga for providing advice from experts in narrow topics, opportunities to learn and a pleasant environment during the writing process.

TABLE OF CONTENTS

ABSTRACT

We use the nighttime light intensity data from the National Oceanic and Atmospheric Administration database to check whether it can be employed as a proxy of economic activity in all the 20 NUTS-3 Baltic regions. Further, the analysis focuses on economic activity convergence in 258 Baltic municipalities. Finally, we indicate the factors that influence the economic activity growth rate in the municipalities.

Our main findings indicate that the nighttime light intensity has a significant relationship with the economic activity in the Baltic NUTS-3 regions, so this measure also can be used to proxy the economic activity level in the Baltic municipalities. We also conclude that there is evidence of the absolute and conditional economic activity convergence presence in the Baltic municipalities. Finally, we find that such factors as the fraction of population at the working age, municipal budget revenue per capita and its growth, the EU fund investments have a positive relationship with the economic activity growth rate, while the population growth, higher crime rate or its growth, as well as the municipality being coastal or a big city, are related negatively.

Keywords: Nighttime light intensity, Absolute convergence, Conditional convergence, Economic activity growth.

I. INTRODUCTION

An increasing number of papers apply satellite data in empirical research, particularly in the field of growth econometrics. Employing satellite data allows studying economic growth process in areas where GDP official data are either unavailable or not precise. The main advantage of using the new satellite approach is that, compared with the conventional approach, to obtain the missing GDP estimates requires only the nighttime light intensity in the area of interest. With a vast improvement in technology, satellites can make images of very high precision. According to the National Oceanic and Atmospheric Administration database (NOAA, 2019), on the older satellite produced images, 1 pixel represented an area of a bit less than 1 square kilometer while newer imagery is even more accurate. NOAA database is publicly available and can be used for research purposes.

Economic activity data, usually measured in GDP or GDP per capita, is one of the main indicators of the living conditions in a particular area. Currently, there is a problem that the economic activity data for Baltic municipalities is not available or collected; hence we were encouraged to study the economic activity levels with a revolutionary approach through nighttime illumination data.

This paper is the first one that provides information about the economic activity in the Baltic countries at the level of municipalities. Despite having other pieces of statistics such as unemployment rate, population level, or amount of investments, it is still vital to have the overall economic activity measurements to assess the living condition of municipalities. For example, the population level in many municipalities in Latgale, one of the Latvian regions, decreases and similarly does the unemployment rate, so the overall trend of the economic activity level there is ambiguous.

Moreover, obtaining the lacking economic activity statistics allows studying another important topic of the economic growth questions – convergence. Since previously there was no data available for the municipal level of GDP per capita, it was also not possible to measure the relationship between the initial economic activity level and its subsequent economic growth. If we find that the nighttime light intensity can be used as a proxy of the economic activity in the NUTS-3 regions for which the official GDP data is available, we would be able to use the same proxy for municipalities. An applicable proxy, in turn, enables us to determine the convergence speed on the municipal level. Apart from the initial economic activity, undoubtedly other factors influence economic growth as well. Indicating these factors is important because it allows determining how to increase the economic activity growth rate where its initial level is low. Several papers are reporting that the speed of beta-convergence tends to be slower at a regional level than at the country level (e.g., Alcidi et al., 2018). In this paper, we check this pattern for the municipalities as well.

Summing up previous paragraphs, we indicate three research questions for this paper:

- **Whether the regional economic activity in the Baltics could be proxied using nighttime light intensity?**
- **Whether the beta-convergence of nighttime light intensity in the Baltics holds at the level of municipalities?**
- **Which factors influence the economic activity growth of the Baltic municipalities apart from the initial economic activity?**

We test the validity of the nighttime light as an economic activity proxy. As a benchmark for economic activity, we use the GDP and GDP per capita measures. The research body of this topic is quite rich at the state level, and most studies confirm that nighttime light intensity is a useful predictor of economic activity, especially where the official data is poor (Elvidge et al., 2007; Henderson, Storeygard and Weil, 2012; Hu and Yao, 2019). On the contrary, substantial progress in subnational studies was initiated only in 2014 by Hodler and Raschky (2014), who find a similar pattern on the regional level. We expand on the studies above and perform similar tests at the municipal level. Our sample includes all 20 Baltic NUTS-3 regions and 258 municipalities. Apart from the nighttime light intensity, we retrieve statistics about demographics, welfare, as well as collect geolocation data through Google Maps.

We estimate regional NUTS-3 economic activity level values by studying nighttime light intensity in each Baltic region. The methodology of obtaining nighttime light intensity will be mostly based on the paper by Henderson et al. (2012). After concluding on the first research question, we estimate the absolute nighttime light intensity convergence speed in the municipalities. We study the pattern deeper and add additional factors that potentially impact the growth rate of economic activity to study the conditional beta-convergence speed. To check the factor significance, we employ both cross-sectional and panel regressions with fixed effects.

Our main findings indicate that the nighttime light intensity has a significant relationship with the economic activity in the Baltic NUTS-3 regions, so this measure also can be used to proxy the economic activity level in the Baltic municipalities. We provide the visual evidence of successful approximation in Figures 1 and 2. We also conclude that there is an evidence of the absolute and conditional economic activity convergence presence in the Baltic municipalities. Finally, we find that certain factors such as the fraction of population at the working age, municipal budget revenue per capita and its growth, EU fund investments have a positive relationship with the economic activity growth rate. In contrast, the population growth, higher crime rate or its growth, as well as the municipality being coastal or a big city, are related negatively.

We contribute to already existing literature by filling several research gaps. Firstly, we check whether the nighttime light intensity data from satellites can be used to estimate the economic activity level in the Baltic municipalities. Our approximation results contribute to the studies by Elvidge et al. (2007), Henderson et al. (2012) and Hu and Yao (2019) by checking the pattern at the lower administrative level – NUTS-3 regions. Secondly, by finding the speed of beta-convergence in the Baltic municipalities, we contribute to the conclusion of the research by Alcidi et al. (2018) who state that the convergence is slower in regions compared to the country level. Another possible contribution is providing insights into how difficult it is for the poorer municipalities in the Baltics to catch up with the richer ones in terms of GDP per capita growth. Our findings related to the convergence contribute to multiple convergence studies, for example, by Zuk et al. (2018) by studying the convergence pattern at the smaller territorial division level of the Baltic countries. Finally, with this research, we also provide opportunities for further research of Baltic municipalities using nighttime lights as a proxy for economic activity. The code for nighttime light data extraction can be replicated in the Google Earth Engine. We provide it in Appendix A.

Further, the paper is structured as follows. Section II describes the existing literature about economic activity proxying through nighttime light intensity and the process of absolute and conditional beta-convergence. In Sections III and IV, we describe the steps of the empirical analysis. Section V presents our analysis and discussion of our results and comparison to the existing literature body. Additionally, we discuss the limitations of this paper. Section VI concludes.

II. LITERATURE REVIEW

2.1 Economic activity proxying

Different methods of proxying economic activity are usually used when the official data is not available. The new approach that appeared relatively recently estimates the GDP per capita with nighttime illumination caused by human economic activity. Muller et al. (2006) are one of the first who study whether the nighttime light intensity is related to the economic activity by looking at the correlation matrices between these two variables. Elvidge et al. (2007) use satellite imagery to study whether they can be used to measure different factors such as population density or economic activity.

Although the authors acknowledge the bright future of satellite systems in terms of gathering this type of information, they point out that the satellite systems of those days lacked spatial resolution. However, Henderson et al. (2012) check whether the nighttime lights can be a good predictor of GDP per capita. The authors claim that the GDP per capita estimate deviates from the official GDP per capita only by three percentage points annually which the authors consider as a quite precise estimate, especially if there is no other way to estimate the official GDP per capita. Moreover, they point out that this approach of estimating GDP per capita allows determining how the income is distributed spatially, i.e. whether a specific area in the country is richer.

Donaldson and Storeygard (2016) summarize previous studies regarding the validity of nighttime light intensity application as proxies for several measures and conclude that the satellite data is a credible source for analysis in many fields including the economic activity. The authors also highlight that the quality of satellite data increases every year, so the estimations made through the nighttime light intensity data should improve from year to year as well. Furthermore, Donaldson and Storeygard (2016) claim that if there is no reliable data about one or another field they consider, the nighttime light intensity data is a valid instrument to be used as a proxy. One such example is a study by Hodler and Raschky (2014) who research regional favoritism of political leaders by looking at the increase in nighttime light activity of the regions where the political leader was born. The authors justify this approach where they claim that the growth in the nighttime light intensity is related to the growth in the real economic activity in the region.

Since many researchers agree that the approach of gathering data through nighttime lights has a big potential, some studies try to improve the method or use the lights a factor for a regression that estimates GDP. For example, Chen (2016) suggests that the factor approach of estimating GDP can be improved having the information about nighttime light intensity. The author run OLS factor regression and tried to estimate GDP in Chinese counties using nighttime light intensity and other different factors, such as illiteracy rate of women, mortality rate, percent of the population working in agriculture, etc. Besides, Chen (2016) use the nighttime light intensity as an instrumental variable in 2SLS regression and find that it also improves the results.

Hu and Yao (2019) use nighttime light intensity to estimate the GDP per capita in every country in the world. They also check how precise the estimation is and find that for the countries with political instability or just poor countries, the model underestimates the level of GDP during a recession. On the contrary, when the situation in such countries stabilizes, the model starts overestimating the GDP data. However, for richer countries where the political condition had been stable, the model shows more precise results that indeed can be used to estimate GDP. However, these systematic deviations can be removed by dividing the sample into groups of countries with relatively equal macroeconomic stability. Since we take three neighboring Baltic countries that are the members of the European Union, we assume that the macroeconomic situation is approximately the same there.

To sum up, the GDP estimation approach that recently appeared deserves attention and is appropriate for this study. Moreover, it is used to estimate GDP in a relatively stable and rich economic region in the after-crisis period, according to Hu and Yao (2019). Thus, the first hypothesis is that the estimated values of the economic activity level will be close to official data using the relatively new approach with nighttime light intensity. We can further compare them and cocnlude if the method can give reliable results. Further, the approach can be applied to estimate economic activity at the municipal level.

2.2 In search of convergence

The term convergence is associated with economic growth and appeared in the middle of the 20th century when the topic of economic development became widely researched. Since there are many types of convergence, we provide several definitions for the convergence types considered in the literature. Firstly, there are beta-convergence and sigma convergence. Alcidi et al. (2018) define beta-convergence across regions as the higher growth rate of a poorer region in terms of GDP per capita compared to a richer one. In turn, sigma-convergence is defined as the decrease of GDP per capita difference over time between the regions. There also exist absolute and conditional beta convergence. Galor's (1995) definition states that the absolute convergence implies different countries growing to the same GDP per capita level in the long run independently of their initial income level. The conditional convergence is defined as countries that have similar characteristics (e.g. investment level, population growth, institutions, etc.) grow to the same GDP per capita level in the long run independently of the initial income level.

After the economic growth theory was formulated, it became a subject of interest. For example, Levine and Renelt (1992) check the correlation between the average share of investment in GDP and the growth rate, as well as approve the convergence pattern. Temple (1999), however, claims that poor countries do not catch up with the rich, and the income distribution becomes polarized to some extent. Additionally, he finds the evidence that although the poor countries do not catch up with the rich ones, they still converge to their steady state at uncertain speed. The author explains this phenomenon with the fact that this type of convergence happens due to foreign technology adoption, and its development had varied much in the previous 30 years. Henderson and Russel (2005) confirm that productivity growth happens because of human and physical capital accumulation. Although they find evidence that international capital flow allows less developed countries to catch up with more developed ones technologically, the authors face difficulty with the effect estimation – different approaches yield different results.

A vital contribution to the theory was made by Barro (1991) who adds different variables to explain the growth of productivity, such as school enrollment, net fertility rate, private investments to GDP, purchasing power parity adjusted GDP deflator, etc. Although the author presents the estimates of the convergence coefficients, he finds a causality problem due to OLS model limitations, so the author acknowledges that some of the results could be questioned.

2.3 Recent studies and the pattern

Although beta convergence of GDP per capita at the municipal level is studied less widely than at the country-level, several studies make an important contribution to our topic. For example, Yang, Zhao and Zhang. (2017) find evidence of convergence presence between the Chinese municipalities. The authors emphasize that the trend has strengthened in the previous years, and it goes in hand with a neoclassical economic growth model. Another finding is related to the fact that the municipalities converge to different steady states due to different geolocation factors, such as proximity to the sea. (Yang, et al., 2017). Dayal-Gulati and Husain (2002) find similar results regarding the presence of beta-convergence in Chinese regions and different steady states for each Chinese municipality.

The economic growth in municipalities was studied in Europe as well. For example, Juessen (2009) studies the economic growth pattern among regions in Germany, focusing on the western and eastern parts of the country. The author concludes that the difference in GDP distribution per worker between western and eastern parts was considerably higher in 1992, but by the beginning of the 21st century, the difference decreased. This implies the beta-convergence presence since the less developed regions managed to catch up with the more developed ones partly. On the contrary, Eicher and Roehn (2007) perform an industry analysis of Germany and claims that the total factor productivity of a country decreased in total. They compare the results with the US, which had experienced an opposite effect and find that the difference in total factor productivity had appeared due to capital shift towards ICT-producing industries in the US.

It was found that the pattern of economic beta-convergence differs at the levels of territorial division. For example, Alcidi et al. (2018) study the convergence speed at different administrative unit levels in the European countries and find that the regional beta-convergence is slower compared than the convergence at the country-level. The authors conclude that the convergence process between capital cities is faster compared to rural areas. This fact might imply that the process is different for the municipalities as well.

The latest studies also show that convergence in European countries is ambiguous. For example, Zuk et al. (2018) find that some of the European countries converge fast, but others do not. The authors also highlight that the financial crisis had slowed the convergence for several European countries, especially Western Balkan countries that could be potential candidates for joining the EU. The authors claim that the beta-convergence process enhancement requires the improvement of the quality of institutions and the increase in investment flows. Alcidi et al. (2018) make similar controversial conclusions about the beta-convergence. In essence, there is a pattern that the convergence exists; however, the evidence showed that the poorest countries might not necessarily have the highest growth rate. The reason for this might be the individual characteristics of the country, which either boost or inhibits the economic growth rate.

To sum up, the convergence pattern exists in today’s economy, and Europe is not an exception. Although the speed of the municipal beta-convergence is likely to be different from the speed at a higher territorial level and several studies indicate the controversy in the convergence process in Europe, the pattern still exists. Thus, we form the second hypothesis that the level of economic activity per capita in the Baltic municipalities has a beta-convergence pattern.

2.4 Factor choice

One of the factors that Solow (1956) and Swan (1956) highlight in their fundamental theory of economic growth is the labor capacity. To account for it in each municipality, we add factors that represent the fraction of the population below, at and above the working age. Barro (1991) was one of the first who adds factors describing population, government budget divided by GDP, investment rate, and political stability of a country, etc. into convergence study. The results show that these factors indeed influence economic growth with positive signs, except the budget-to-GDP factor, which has a negative relationship with the economic growth rate. Temple (2009) highlights that macroeconomic stability and growth itself might partially depend on investments. Apart from including foreign direct investments, our study also accounts for the special investments from the European Union funds, which is another type of investments. Temple (2009) also argues that the speed of growth differs across countries due to their legislation - countries that have a higher degree of economic freedom tend to grow faster. Easterly and Levine (1997) study the growth of African countries and find that due to the same factor of political instability, which brings to all its consequences including worse social conditions and increased crime rate, the growth slows down.

A spatial approach in econometrics can be applied to study the convergence. Südekum (2003) maps the differences between European country regions using several indicators, such as the number of patents, employment growth, GDP per employed person, etc. LeSage and Fischer (2008) show that the regional economic growth rate also depends on the economic level of the neighboring regions. The more spatially connected and dependent the regions are, the stronger is the relationship. Yang et al. (2017) highlight that the spatial approach applied for Chinese provinces reveals the absolute and conditional beta-convergence patterns. It opens insights of differences in the steady states of the regions. Moreover, the research indicates that some macroeconomic policy changes were implemented to boost the economic development in poorer regions, and the results of the study show that they were successful. The beta-convergence speed increased for initially poorer provinces, and they started catching up with the more developed ones (Yang et al., 2017).

Different constant factors can also be a reason for deviation in beta-convergence speed across regions. Moreover, one of the factor categories that do not change over time is the geographical factors category. Bao et al. (2002) find that such factors as the length of coastline or the distance to it explain the differences in growth across provinces to some extent. Demurger (2001) also studies the geolocation influence on the provincial growth rate and concludes that it is one of the reasons for deviation in economic growth rates. Christ (2012) combines a spatial approach with fixed factors by adding dummy variables for the country, urban territory, as well as marking the regions with capitals. His findings show that these variables are statistically significant in influencing the GDP per capita growth. Overall, Cuaresma and Silgoner (2014) find that fixed effects, including the constant factor categories such as geolocation factors, add consistency to estimating the speed of beta-convergence. We also expand on the aforementioned papers by constructing geolocation factors that were not previously studied but could be relevant for the current situation in the Baltic municipalities, such as the dummy representing that the municipality is a border of the European Union.

Previous studies suggest a large number of methods and factors on how to study the convergence. In combination with factors constructed by us, namely several geolocation factors, we propose the third hypothesis that all these factors are significantly related to the economic activity growth rates in line with indicated signs. We present the summary of the factors we test as well as the expected signs below.

Demographic factors:

- Population ($Population_{i,t}$, +);
- Population growth ($PGrowth_{i,t}$, -);
- Fraction of population below working age ($belowWA_{i,t}$, -);
- Fraction of population at working age ($atWA_{i,t}$, -);
- Population density ($Density_{i,t}$, +).

Welfare factors:

- Municipal budget revenue per capita ($Budget_{i,t}$, +);
- Municipal budget revenue per capita growth ($BGrowth_{i,t}$, +);
- Criminal cases per capita ($Crime_{i,t}$, -);
- Growth of criminal cases ($CGrowth_{i,t}$, -).
- Foreign direct investments per capita ($Investments_{i,t}$, +)
- Investments from the European Union funds per capita ($EUFunds_{i,t}$, +)

Apart from the dummy variable representing the country and whether the municipality is a large city (defined as a city with a population more than 25,000), we use Google Maps to construct several additional geolocation factors:

Geolocation (spatial)

- Country dummy ($Country_{i,}$);

factors:

- Large city dummy (*$LargeCity_i$, -)*;
- Region dummy (*$Region_i$,)*;
- Distance to a large city in kilometers (*$DistLargeCity_i$, -)*;
- Time to reach a large city by car (*$TimeLargeCity_i$, -)*;
- Distance to the capital in kilometers (*$DistCapital_i$, -)*;
- Time to reach the capital by car (*$TimeCapital_i$, -)*;
- EU border dummy (*EU_i, -)*;
- Coastal area dummy (*$Coast_i$, -)*.

There are more factors that could provide further insight into convergence patterns in our sample apart from listed in the table. However, the data availability for municipalities is highly constrained; hence some factor data could only be obtained to selected countries, for example, investments from the EU funds. For many factors the data is unavailable at all, for example, we were not able to find several factors by municipalities from Barro (1991), such as the educational quality, fertility rate or the municipal budget divided by its GDP. We also consider several traffic factors, such as the road density in the municipalities or traffic intensity; however, there is no representative data.

III. DATA

3.1 Subnational unit statistics

The area of our focus is NUTS-3 regions and local municipalities of the three Baltic States during the period from 2010 to 2018. We select this period to eliminate the volatility of the crisis in 2008-2009 while the upper bound is subject to official GDP statistics availability at the regional level. Following the Nomenclature of territorial units for statistics (NUTS) provided by the Eurostat (2019), our study regions, therefore, are NUTS-3 regions and Local Administrative Units (LAU). Overall, there are 20 NUTS-3 regions and 258 Local Administrative Units; also, we provide a brief study area summary in Table 1 below. In further sections, we interchangeably use NUTS-3 regions as “regions”" and Local Administrative Units as “municipalities”.

Area	Latvia	Lithuania	Estonia	Total
Regions (NUTS-3)	5[1]	10	5	20
Municipalities (LAU)	119	60	79	258

Table 1. Territorial administrative division of the Baltic countries. Created by the authors using data from official statistics authorities.

We include NUTS-3 regions to our study to answer the first research question because the official GDP statistics for municipalities (LAU) is not available. To extract the latest geographical division of regions and municipalities, we use the official government agencies who provide such information.

The official statistical authorities of Latvia, Lithuania, and Estonia provide information on most conventional economic variables we test in the second part of the research. For some of the welfare variables for Latvian municipalities, we employ State Regional Development Agency (SRDA) data while for geolocation factors, we rely on Google Maps. In Appendix B, we present the descriptive statistics table for all variables used, and also, we provide the sources for each variable in Appendix C.

3.2 Nighttime lights

The National Oceanic and Atmospheric Administration (NOAA) produces monthly composites of nightlight satellite imagery. The weather satellite captures light images every day during a fixed time interval throughout the year, and furtherly produces an adjusted composite cleared from the impact of clouds, gas flares, and other background noise (NOAA,

[1] We use SRDA classification for Latvian NUTS-3 regions who aggregate data by 5 statistical regions.

2019). During our research period, around 2014, an older U.S. Air Force Defense Meteorological Satellite with a Program Operational Linescan System (OLS) was replaced by Visible Infrared Imaging Radiometer Suite (VIIRS) equipped on a newer satellite (NOAA,2019). The DMSP data is annual while both annual (when available) and monthly composites are accessible for VIIRS observations; therefore, we take annual composites where possible. For the most recent VIIRS data, annual composites are not yet generated, so we calculate the average of monthly composites to arrive at yearly values. We integrate the data from NOAA and subnational borders using Google Earth Engine.

Further, we follow the principle that nighttime illumination usually stems from human economic activity; therefore, it has a high positive correlation with the official GDP measures both at national and subnational levels (Doll et al., 2006; Henderson et al., 2012; Hodler and Raschky, 2014). One of the satellite imagery beneficial features is the possibility to capture lights in areas in size up to around one square kilometer.

Each pixel represents an area around one square kilometer and has its radiance parameter represented by a number from 0 (the darkest) to 63 (the brightest). The new VIIRS sensor, however, uncapped the radiance parameter to prevent top-coded pixels in the most developed areas. For our analysis, we employ two common approaches to consolidate pixel brightness by every region – average pixel brightness in one square kilometer in the area (Henderson et al., 2012) and the sum of pixel brightness by area (Hu and Yao, 2019). For notational purposes, we report average pixel brightness as average lights but the sum of pixel brightness as total lights. Consequently, we take the natural logarithms of both measures and create variables $RLights_{i,t}$, $RLightsAVG_{i,t}$, and $MLights_{i,t}$, $MLightsAVG_{i,t}$ for regional and municipal lights, respectively.

We detect five municipalities[2] that had both total and average nightlights of 0 in certain years and could not be log-transformed. Since in these respective years the aforementioned municipalities still had officially registered populations, we cannot argue that there was no economic activity; hence we adjust total and average nightlights for municipalities by +0.01 as suggested by Michalopoulos and Papaioannou (2013). Our main results, however, are robust to the panel without these adjustments as we briefly present in Appendix D. For regional lights data such adjustment was not required.

Finally, we illustrate how the overall night-time illumination picture has changed over the period 2010-2018. We provide 2 sample areas – Latvia as an example for a country

[2] These five municipalities are Rugāju, Vārkavas in Latvia, and Kihnu, Ruhnu, Vormsi in Estonia

(Figures 1 and 2) and Jēkabpils municipality for illustration of a municipal area (Figures 3 and 4).

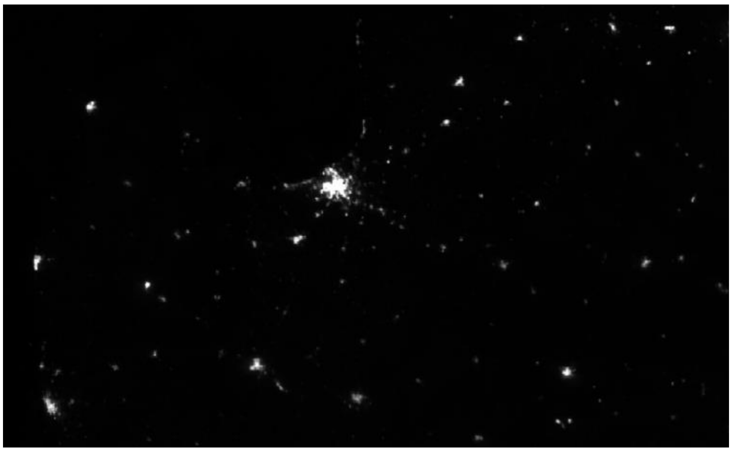

Figure 1. Nighttime lights in Latvia in 2010. Created by the authors using data from NOAA (2019).

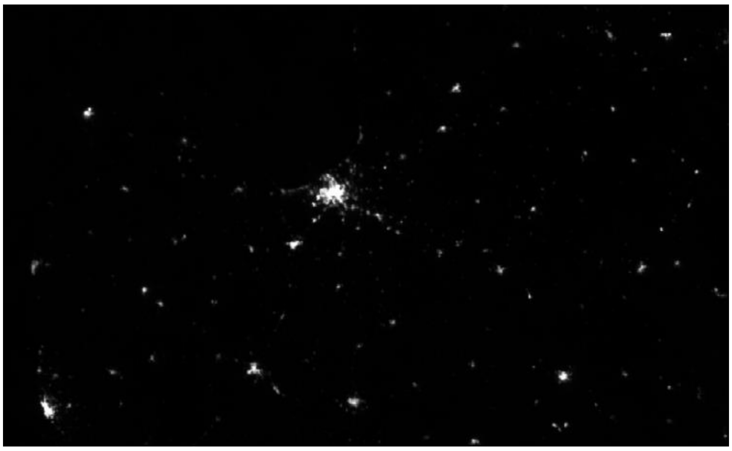

Figure 2. Nighttime lights in Latvia in 2018. Created by the authors using data from NOAA (2019).

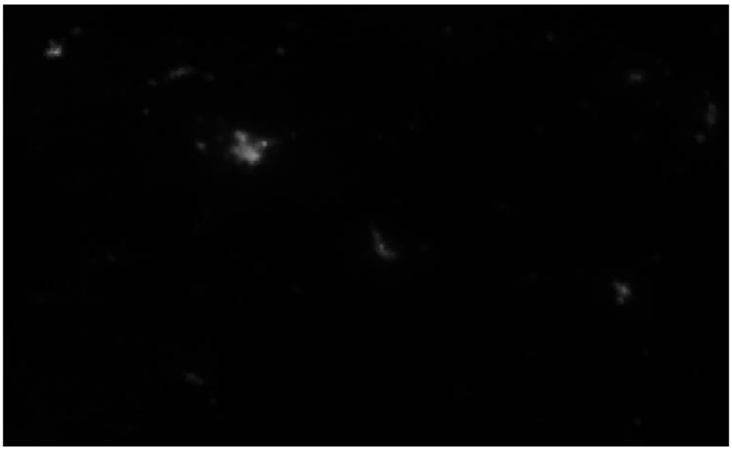

Figure 3. Nighttime lights in Jēkabpils municipality in 2010. Created by the authors using data from NOAA (2019).

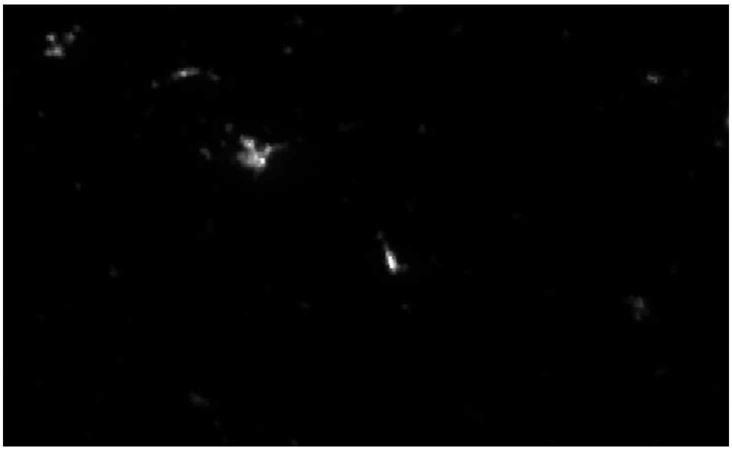

Figure 4. Nighttime lights in Jēkabpils municipality in 2018. Created by the authors using data from NOAA (2019).

As one can expect, the difference is not readily observable from the static imagery because nine years is a rather short period to see noticeable macroeconomic advancements; however, an evident difference is in the less developed areas. Comparing Figures 1 and 2 we see no stark changes for the Riga municipality (the brightest area in the center of a figure) as well as for the other larger cities, but the smaller regions, especially the ones located along the river Daugava became clearly visible. In Figures 3 and 4 below, we demonstrate an example of less developed areas to increase their economic activity intensity as the nighttime illumination became brighter since 2010.

IV. METHODOLOGY

4.1 Proxying economic activity

We divide our research into several parts. In the first part of our study, we test the nighttime lights intensity suitability for economic activity level proxying for the NUTS-3 regions in line with the method first suggested by Henderson et al. (2012) due to the absence of official GDP statistics on municipalities. We collect the nighttime lights data through Google Earth Engine, where one can specify any level of pixel-data aggregation given the borders are defined. For example, by uploading city borders from external resources, it is possible to specify to collect data only within this city borders. We provide our Google Earth Engine code in Appendix A as a framework for nighttime light data collection.

To account for inflation and purchasing power differences, we adjust GDP data according to Eurostat PPP data, which is available at the country level. To verify strong relation between regional GDP and nighttime light intensity shown by Henderson et al. (2012) at a state level and others at a subnational level (e.g., Doll et al., 2006; Michalopoulos and Papaioannou, 2013; Hodler and Raschky, 2014), we employ a linear specification:

$$RLights_{i,t} = \beta_0 + \beta_1 RegionalGDP_{i,t} + \beta_2 Year_t + \varepsilon_{i,t}, \qquad (1)$$

where $RLights_{i,t}$ variable is regional log-transformed total pixel intensity in region i in year t; $Year_t$ denotes year dummy for time-fixed effects; $RegionalGDP_{i,t}$ is log-transformed GDP of a NUTS-3 region, and $\varepsilon_{i,t}$ is a random error term.

Accounting for time-fixed effects is essential in this specification due to the sensor settings variations and the whole satellite change around 2014 (see Section 3.2). We expect a linear relationship between regional GDP and light intensity given Henderson et al. (2012) and Hodler and Raschky (2014) get similar elasticity coefficients in obtained coefficients for this relationship both on national and subnational levels.

We also consider two alternative specifications of (1) stemming from the research design of Henderson et al. (2012). One alteration involves substituting total regional pixel intensity by the average pixel intensity per region to test whether we get similar results to the original paper. In another alteration, we replace nighttime light intensity by total electricity consumption $RElectricity_{i,t}$ following from the nature of illumination (Henderson et al., 2012). According to the authors, the electricity consumption data increases the explanatory power of the model. However, we are restricted having such data only at a regional level while satellite data is uniformly available for all municipalities in our sample.

Finally, relating to the second part of the paper where we study convergence among Baltic municipalities, we explore the nighttime light intensity concentration patterns across respective countries. The common approach is to observe the Herfindahl-Hirschman Index (HHI) fluctuations, so we use it as a measure for nighttime light intensity concentration (Rhoades, 1993; Hannan, T. H., 1997). However, the year-specific effects caused by different satellites drastically distort the HHI measure, and we use the changes of the relative weight of total nighttime light intensity in large cities (defined as cities with a population larger than 25,000) as a measure for light concentration.

4.2 Convergence study

In the second part, we study how pronounced is the absolute and conditional beta-convergence among municipalities of the Baltic countries. To study absolute convergence existence, we take the relative growth of municipality nighttime light intensity ($MLights_{i,t}$) and regress the newly created variable $MLGrowth_{i,t}$ on the initial light intensity per capita at the beginning of the year.

$$MLgrowth_{i,t} = \beta_0 + \beta_1 MLights_{i,t} + a_i + \varepsilon_{i,t}, \tag{2}$$

where $MLGrowth_{i,t}$ is relative growth of log-transformed total pixel intensity per capita in municipality i in year t; $MLights_{i,t}$ is log-transformed municipal total pixel intensity per capita; a_i denotes country and satellite fixed effects; $\varepsilon_{i,t}$ is a random error term.

For the conditional beta-convergence study, we use two models - ordinary least squares in cross-section and panel regressions with fixed effects. We also add fixed effects to capture all the potentially known or unknown constant factors that affect the economic activity growth rate in the Baltic municipalities, and, according to Cuaresma and Silgoner (2014), adding fixed effects should improve the convergence model. Moreover, we estimate the following equations only in linear terms because the previous works do not find useful to include the quadratic term to the regression. We verify conditional beta-convergence by including various economic factors denoting them as $Factors_{j,i,t}$ and run the following model:

$$MLgrowth_{i,t} = \beta_0 + \beta_1 MLights_{i,t} + \beta_j Factors_{j,i,t} + a_i + \varepsilon_{i,t}, \tag{3}$$

where $Factors_{j,i,t}$ are various economic factors (j is the factor number) which include all the welfare and demographic factors listed at the end of section II. Other variables remain the same as in specification (2).

We employ a cross-section approach to check the significance and elasticities of different factors in the medium run, namely, from 2011 to 2017. Although we retrieve the data from 2010 to 2018 for the nighttime light intensity, the official statistics provide data only until 2017, so the conditional convergence can be studied only until 2017. Moreover, we use values for 2010 are used to calculate the growth rate for 2011, so technically, our dataset captures the years from 2011 to 2018. With this approach, it is possible to capture marginal effects of different fixed factors that remain constant over time, for example, geolocation factors, such as distance to the capital city or whether the municipality is near the sea. The dependent variable is the natural logarithm of nighttime light intensity per capita growth during the six years. The independent variables are the initial nighttime light intensity per capita in 2011, several factors added by Barro (1991) and Bao et al. (2002), such as investment level or population structure and growth. Also, we consider different dummy variables representing the location features, as performed by Demurger (2001) and Christ (2012). The linear specification for the medium run is the following:

$$MLgrowth_{i,t} = \beta_0 + \beta_1 MLights_{i,t} + \beta_j Factors_{j,i,t} + \beta_g Location_{g,i,t} + \varepsilon_{i,t}, \quad (4)$$

where $Location_{g,i,t}$ are various spatial factors (g is the factor number) and other variables remain the same as in specification (3).

V.ANALYSIS AND DISCUSSION

5.1 Proxying economic activity

In line with Section IV, we proceed to an analysis of economic activity proxying using nighttime lights intensity (*RLights*$_{i,t}$) and officially reported GDP of Baltic NUTS-3 regions (*RegionalGDP*$_{i,t}$).

We present the visual evidence of regional GDP approximation with nighttime lights in Figures 5 and 6 below. The map on the left shows regional GDP per capita, while the map on the right shows average nighttime light intensity per region (measured in average pixel brightness). We explain our nighttime light data aggregation methods in Section 3.2. Excluding slight differences in economic activity distribution, the lights well capture the regions which are more developed if benchmarked by GDP. In Appendix E, we also show that alternative GDP and light measures for approximation work just as well.

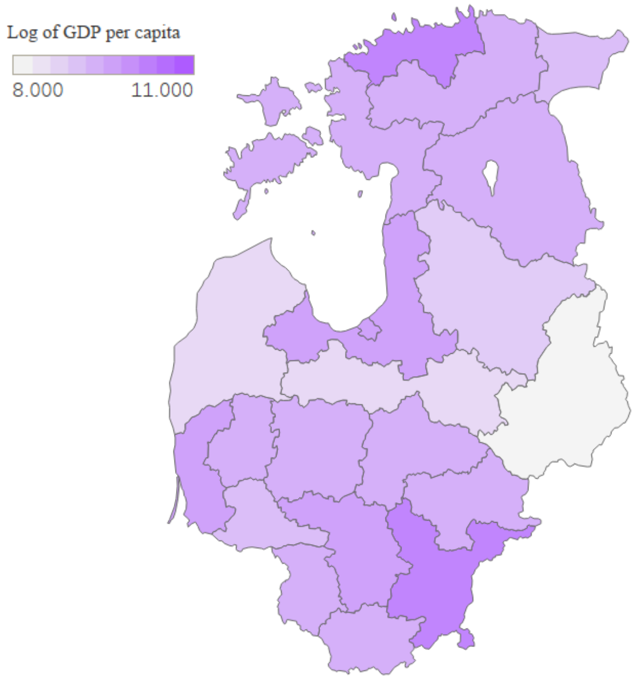

Figure 5. Regional economic activity proxied with the log of GDP. Created by the authors using data from official statistics authorities.

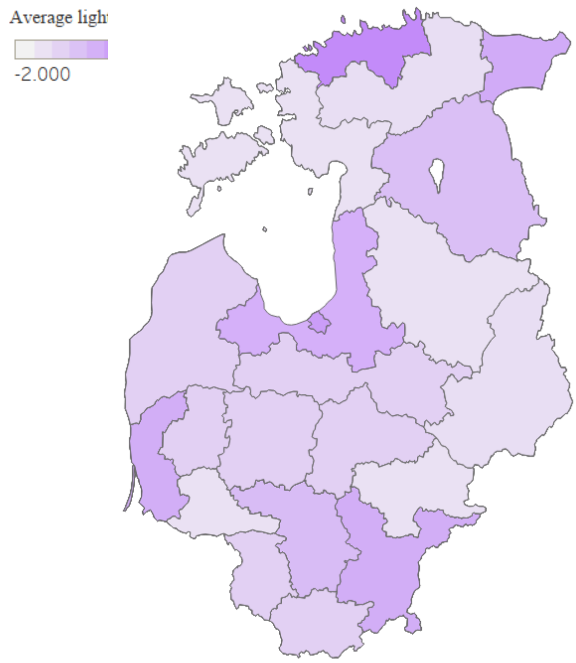

Figure 6. Regional economic activity proxied with the log of average regional nighttime light intensity. Created by the authors using data from NOAA (2019).

For the formal analysis, we present various specifications of the first (1) equation in Table 1 below. To account for various year-related effects such as satellite change, we add year-fixed effects into the model.

The main results show that the nighttime light intensity in the Baltic regions from 2010 to 2018 indeed has a statistically significant relationship with economic activity. Column (1) represents the relationship between the absolute values of nighttime light intensity per capita and regional GDP per capita, both taken in the natural logarithms. The elasticity of the regression coefficient is equal to 0.301, which is considerably lower than the state-level estimates of Hu and Yao (2019), yet the coefficient is strongly significant. Based on high explanatory power of 0.84 and high statistical significance, we conclude that nighttime lights are indeed a useful proxy for economic activity in the Baltics.

This table reports linear regression using annual data for NUTS-3 administrative units in the Baltic States during 2010-2018. $RegionalGDP_{i,t}$ is the log of regional GDP. $RLights_{i,t}$ is the log of total nighttime light intensity. $RLightsAVG_{i,t}$ is the log of average nighttime light intensity. $RElectricity_{i,t}$ is the log of regional electricity consumption measured in KWH. Adjusted R^2s do not include the variance explained by the fixed effects. Standard errors are clustered both by region and year, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Variable	$RegionalGDP_{i,t}$ (1)	$RegionalGDP_{i,t}$ per capita (2)	$RegionalGDP_{i,t}$ Latvia (3)	$RegionalGDP_{i,t}$ per capita Latvia (4)	$RegionalGDP_{i,t}$ Latvia (5)
$RLights_{i,t}$	0.301*** (0.038)		0.363*** (0.022)		
$RLightsAVG_{i,t}$		0.851*** (0.086)		0.840*** (0.100)	
$RElectricity_{i,t}$					1.582*** (0.050)
Number of regions	20	20	5	5	5
Observations	175	175	40	40	40
Adjusted R^2	0.839	0.831	0.981	0.913	0.968
Fixed effects	Year	Year	Year	Year	Year

Table 2. Nighttime lights as a proxy for economic activity in Baltic regions. Created by the authors using data from NOAA (2019) and official statistics authorities.

Further, in column (2), we employ a similar model studied by Henderson et al. (2012) by using the average pixel brightness by region instead of total lights by region. We also switch to GDP per capita as the dependent variable. By testing a slightly altered measure, we mainly look for both robustness checks in general and in case the population data is imprecise, which especially can happen with municipality statistics. We arrive at a strongly significant coefficient of 0.851 which is somewhat larger than in the original paper. However, our reported explanative power is high which is in line with of that reported by Henderson et al. (2012) or Hodler and Raschky (2014).

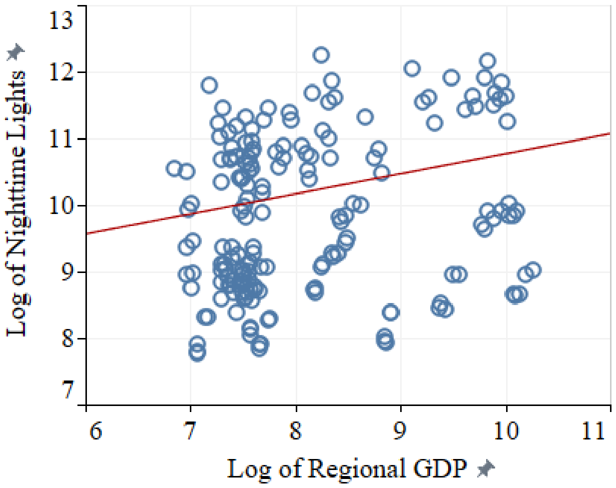

Figure 7. Scatterplot between the log of regional GDP and total regional nighttime lights. The trendlines are adjusted for the approximate average year-fixed effects. Created by the authors using data from NOAA (2019) and official statistics authorities.

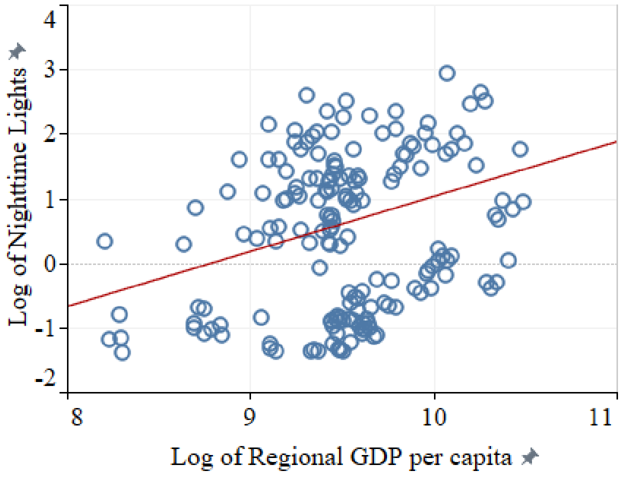

Figure 8. Scatterplot between the log of regional GDP per capita and average regional nighttime lights. The trendlines are adjusted for the approximate average year-fixed effects. Created by the authors using data from NOAA (2019) and official statistics authorities.

We explore the relationship further by plotting both variables in Figure 7 and Figure 8. Figure 7 features the relationship of the log of total nighttime light intensity and log of total GDP (column 1), whereas Figure 8 illustrates the relationship of the average GDP nighttime light intensity per pixel in the area with the GDP per capita (column 2) We find support for the pattern in Figure 7 from Hu and Yao (2019), who also observe a similar relationship. Figure 8, on the other hand, shows that average lights and regional GDP per capita have the same pattern, as demonstrated by Hodler and Raschky (2014), who also study regional administrative units.

One may note that another predictor of economic activity could be electricity consumption data because most of the night illumination certainly requires electricity. To compare the relative effectiveness of nighttime lights for proxying purposes, as suggested by Henderson et al. (2012), we substitute light intensity with electricity consumption data ($RElectricity_{i,t}$) measured in KWH per region. Due to data scarcity, which is a serious obstacle with electricity data in general, we can compare both approaches only for Latvia hence significantly restricting our sample. We report the results with electricity in column 5, while presenting a comparable result with total lights intensity per capita in column 4.

The regression results in column 3 show that the relationship between the total nighttime light intensity per and total GDP is also significant for Latvian regions only. At the same time, as reported in column 5, total electricity consumption can also explain GDP in Latvian regions just as well considering strong explanative powers of both. Consequently, we conclude that nighttime lights approximate economic activity similar as electricity consumption, which is similar to the conclusions of Henderson et al. (2012). Moreover, the overall unavailability of electricity data (in our case, the data was available only for Latvia) makes nighttime lights a preferable proxy for economic activity.

For a better comparison, in column 4, we report comparable measures using average pixel brightness per region. Both electricity consumption and total lights per capita have better yet marginal explanative power to the model. Therefore, for consistency, in the next section, we use only total pixel brightness per capita as the proxy of the economic activity level.

Thus, the conclusions of previous studies at the national level also hold at a NUTS-3 level in the Baltics, and the answer to the first research question is positive - the economic activity in the Baltic regions can be approximated using the nighttime light intensity.

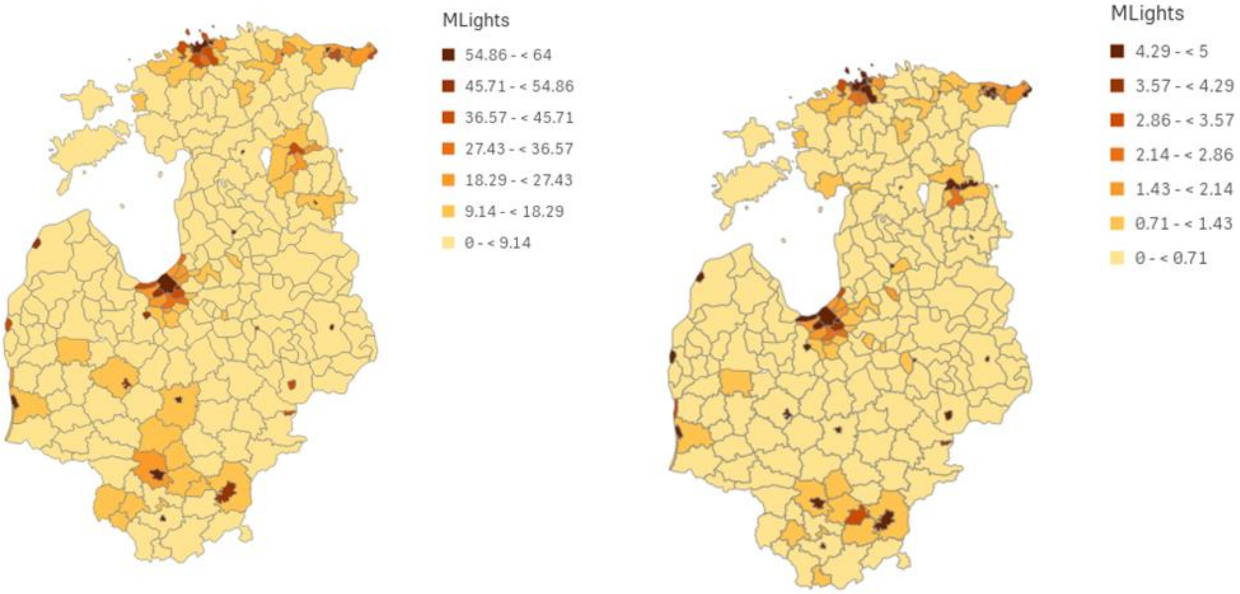

Figure 9. Nighttime light geographical distribution among Baltic States' municipalities (year 2010 on the left, year 2018 on the right). Created by the authors using data from NOAA (2019).

We take the first glance into the recent convergence development in our study region. In Figure 9, we provide a visual representation of nighttime light distribution among Baltic municipalities in the years 2010 and 2018. The higher economic activity level is associated with a darker color which persists mostly in large cities. For example, the north of Estonia, where its capital Tallinn is located, has a noticeably darker color compared to its southern parts consisting mostly of district areas.

For a clearer picture, we quantify the municipal concentration of nighttime lights by taking the percentage change (relative change) of nighttime light concentration in large cities from the first (1) specification.

The overall trend shows that the change in the nighttime light intensity is negative for the large cities, which implies that the more developed areas have a slower growth rate in general. This should mean that the convergence patterns exist, which we check in further analysis. The annual change in relative nighttime light intensity is shown in Figure 10. The general trend is observable; however, it is clear that the satellite change in 2014 effect could not be wiped out completely. For a clearer picture, in Figure 11, we restrict the timeframe to 2015-2018 to keep only one satellite; otherwise, the estimates deviate due to the different satellite characteristics.

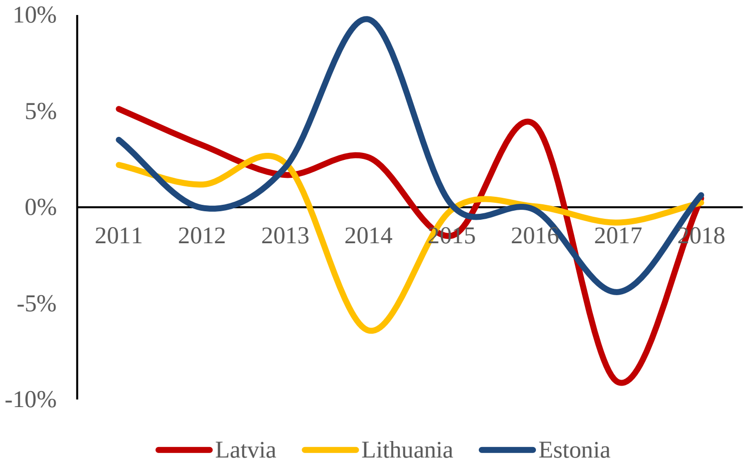

Figure 10. Relative change of the proportion of total nighttime light intensity in large cities by Baltic countries (2011-2018) measured in logs. Created by the authors using data from NOAA (2019).

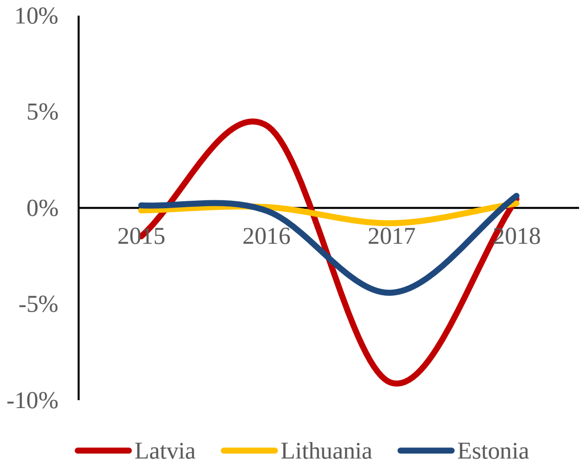

Figure 11. Relative change of the proportion of total nighttime light intensity in large cities by Baltic countries (2015-2018) measured in logs. Created by the authors using data from NOAA (2019).

5.2 Beta-convergence

The next subject of study was to find whether there exists an absolute beta-convergence of the economic activity among the Baltic municipalities. Considering the previous finding that the nighttime light intensity is a predictor of economic activity for the Baltics, we use it as a proxy of the economic activity instead of the GDP data which is currently unavailable at the level of municipalities. To find whether the convergence of the economic activity exists, we take the nighttime light intensity per capita measure with the yearly growth of the same measure and run a panel regression with fixed effects. The results summarized in Table 3 show that the convergence pattern indeed exists. The results for the whole sample represented in column 1 can be interpreted as follows: if the initial level of nighttime light intensity per capita is higher by 1% in a certain municipality, the growth rate of the nighttime light intensity per capita in this municipality gets slower by 0.150%. The values for Latvian (column 2), Lithuanian (column 3) and Estonian (column 4) municipality samples are 0.832%, 1.177%, and 0.167% respectively using the same interpretation. The sample that included all 3 Baltic countries has the lowest coefficient due to the higher constant term. Alcidi et al. conclude that the speed of convergence is at least 2% yearly at the country. Our results show that the economic activity convergence at the municipal level is slower.

This table reports panel regression using annual data for local administrative units (LAU) in the Baltic States during 2011-2017. $MLgrowth_{i,t}$ is the relative increase the of total municipal nighttime light intensity per capita. $MLights_{i,t}$ is the total municipal nighttime light intensity per capita in the respective year. Standard errors are clustered both by municipality and year, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Variable	All countries (1) $MLgrowth_{i,t}$	Latvia (2) $MLgrowth_{i,t}$	Lithuania (3) $MLgrowth_{i,t}$	Estonia (4) $MLgrowth_{i,t}$
$MLights_{i,t}$	-0.150*** (0.049)	-0.832*** (0.160)	-1.177*** (0.171)	-0.167*** (0.056)
Number of municipalities	258	119	60	79
Observations	1,866	833	480	553
Fixed effects	Yes	Yes	Yes	Yes

Table 3. Absolute beta-convergence in Baltic municipalities. Created by the authors using data from NOAA (2019) and official statistics authorities.

This implies that absolute convergence exists in the Baltic municipalities or, using Galor’s (1995) definition, the Baltic municipalities grow to the same economic activity level in the long run independently of their initial conditions. This matches the conclusion made by Yang et al. (2017) that convergence exists at the municipal level. Moreover, the findings coincide with the results of Zuk et al. (2018) and Alcidi et al. (2018) who indicate the convergence presence in the European countries; however, its speed at the level of municipalities is lower compared to the regional level considered by these authors and differs across the countries. For example, the results show that the convergence in Lithuania is considerably faster than in Estonia. Also, this complements the results of Zuk et al. (2018) regarding the claim that different European countries have different convergence speed.

The findings of this paper indicate that the differences in convergence speed exist at the level of municipalities as well, while the municipal convergence speed is slower compared to the findings of Zuk et al. (2018) and Alcidi et al. (2018) where the average growth rate of the tested countries and regions was about 2%.

Apart from the absolute convergence existence across the Baltic municipalities, the conditional convergence patterns were also considered. We examine different factors that could influence the economic activity convergence speed and conclude that the conditional convergence across the Baltic municipalities exists as well.

As in part with an absolute convergence check, we also run a panel regression with fixed effects for the whole sample together and for each country separately, but this time some other factors are added. In addition, because urban areas might have different economic development patterns, we exclude the municipalities with cities where the population number was higher than 25 000 people and run the same regression. The results are summarized in Table 4 and Table 5.

The results show that the conditional convergence speed is the highest in Lithuania (column 3)with the coefficient of approximately -1.6 versus -0.8 and -0.1 for Latvia (column 2) and Estonia (column 4) respectively which is considerably lower than country-level convergence equal to 2% as it is found by multiple studies including Alcidi et al. (2018). In addition to being slow, the convergence speed in Estonia is also significant only using the 10% significance threshold.

Overall, apart from the initial level of nighttime light intensity per capita, the significant factors influencing the economic activity growth rate we find are population growth rate (-), which goes in line with the neoclassical economic growth model, municipal budget size per capita (+), the growth of it (+). Also, the fraction of population below the working age in the municipality (-), which is related to the theory of Solow (1956) and Swan (1956), EU fund investments (+) and criminal cases per capita in the municipality (-) which are related to the findings of Temple (2009) and Barro (1991).

Although for some samples several factors were insignificant, for example, the municipal budget revenue per capita in the sample with all three countries and Estonia separately, or the fraction of population below the working age in Lithuania, they still show significance in other regressions in the table. Such factors as population density or investments per capita were also tested; however, the model showed insignificant results for each of the Baltic countries.

These findings contribute to our second and third hypotheses, as well as the second and third research questions by providing an insight about the factors that influence the economic growth in the Baltic municipalities confirming the presence of convergence pattern there.

This table reports the panel regression using the annual data for local administrative units (LAU) in the Baltic States during 2011-2017. $MLgrowth_{i,t}$ is the relative increase of the nighttime light intensity per capita. $MLights_{i,t}$ is the initial level of nighttime light intensity per capita of the respective year. $Pgrowth_{i,t}$ is the relative increase of the municipal population. $belowWA_{i,t}$ is the fraction of population below the working age. $Budget_{i,t}$ is the municipal budget revenue per capita. $Bgrowth_{i,t}$ is the relative increase of the municipal budget revenue per capita. $EUFunds_{i,t}$ is the investments per capita from the EU funds. Standard errors are clustered both by municipality and year, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Variable	All countries (1) $MLgrowth_{i,t}$	Latvia (2) $MLgrowth_{i,t}$	Lithuania (3) $MLgrowth_{i,t}$	Estonia (4) $MLgrowth_{i,t}$
$MLights_{i,t}$	-0.233*** (0.055)	-0.839*** (0.182)	-1.550*** (0.202)	-0.106* (0.063)
$Pgrowth_{i,t}$	-2.143*** (0.416)	-8.636*** (2.041)	-17.142*** (2.192)	-1.354*** (0.399)
$belowWA_{i,t}$	-5.913*** (1.414)	-5.891** (2.722)	Omitted due to insignificance	-7.841*** (1.837)
$Budget_{i,t}$	Omitted due to insignificance	0.531*** (0.179)	0.338** (0.135)	Omitted due to insignificance
$Bgrowth_{i,t}$	0.768*** (0.106)	1.109*** (0.161)	0.604*** (0.200)	0.441* (0.265)
$EUFunds_{i,t}$	Omitted due to data unavailability	0.117*** (0.031)	Omitted due to data unavailability	Omitted due to data unavailability
Number of municipalities	258	119	60	79
Observations	1529	714	420	395
Fixed effects	Yes	Yes	Yes	Yes

Table 4. Conditional convergence in Baltic municipalities (2011-2017). Created by the authors using data from NOAA (2019) and official statistics authorities.

We also exclude municipalities with big cities where the population was higher than 25 000 people, and the results are summarized in Table 5. The columns represent the same samples, and all the factors only slightly changed their coefficient without changing sign or significance. The only exception was Estonia, where the coefficient representing the light becomes insignificant even at the 10% level. However, overall the results are not surprising because we included the region fixed effects in these regressions as suggested by Cuaresma and Silgoner (2014)[3].

This table reports the panel regression using the annual data for local administrative units (LAU) in the Baltic States during 2011-2017. $MLgrowth_{i,t}$ is the relative increase of the nighttime light intensity per capita. $MLights_{i,t}$ is the initial level of nighttime light intensity per capita of the respective year. $Pgrowth_{i,t}$ is the relative increase of the municipal population. $belowWA_{i,t}$ is the fraction of population below the working age. $Budget_{i,t}$ is the municipal budget revenue per capita. $Bgrowth_{i,t}$ is the relative increase of the municipal budget revenue per capita. $EUFunds_{i,t}$ is the investments per capita from the EU funds. Standard errors are clustered both by municipality and year, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Variable	All countries (1) $MLgrowth_{i,t}$	Latvia (2) $MLgrowth_{i,t}$	Lithuania (3) $MLgrowth_{i,t}$	Estonia (4) $MLgrowth_{i,t}$
$MLights_{i,t}$	-0.206*** (0.058)	-0.861*** (0.182)	-1.545*** (0.232)	-0.097 (0.066)
$Pgrowth_{i,t}$	-2.048*** (0.431)	-8.516*** (2.163)	-16.681*** (2.402)	-1.360*** (0.408)
$belowWA_{i,t}$	-5.726*** (1.520)	-6.351** (2.888)	Omitted due to insignificance	-7.908*** (1.934)
$Budget_{i,t}$	Omitted due to insignificance	0.528*** (0.195)	0.306** (0.154)	Omitted due to insignificance
$Bgrowth_{i,t}$	0.878*** (0.115)	1.170** (0.174)	0.692*** (0.234)	0.464* (0.271)
$EUFunds_{i,t}$	Omitted due to data unavailability	0.136*** (0.037)	Omitted due to data unavailability	Omitted due to data unavailability
Number of municipalities	233	110	49	74
Observations	1373	660	343	370
Fixed effects	Yes	Yes	Yes	Yes

Table 5. Conditional convergence in Baltic municipalities excluding large cities (2011-2017). Created by the authors using data from NOAA (2019) and official statistics authorities.

Summing up the obtained results, they partially coincide with previous theoretical findings. The factor which represented the number of criminal offences per capita can be attributed to social stability - also considered by Barro (1991). Moreover, the factor representing the population growth rate has a negative sign in the model which coincides with the neoclassical economic growth model of Solow (1956) and Swan (1956). The fraction of the population below the working age represents the structure of population which was later added by Barro (1991), who also contributed to the neoclassical economic growth model development. The negative sign obtained in this research coincides with Barro’s (1991) results.

[3] Since the municipality being a large city is a constant factor, the regression should account it in the fixed effects part. However, we add this dummy separately in the cross-section regressions

We run the cross-sectional regressions summarized in Table 6 to check the medium run conditional convergence in the Baltic municipalities and obtain that the convergence exists. There is a negative relationship between the initial nighttime light intensity in 2011 and its growth rate from 2011 to 2018. Moreover, the following factors are significant in the regression: the fraction of the population at the working-age (+), municipal budget revenue per capita (+) and criminal rate growth (-). The resulting signs of the following factors are in line with the respective studies: the fraction of population at the working age - Solow (1956) Swan (1956), criminal rate growth – Temple (2009). Additionally, we check several factors constant over time including the spatial factors, and we find that such factors as the coastal dummy (-), large city dummy (-), and time to the capital (+) significantly influence the economic activity growth rate. The result regarding the coastal and large city dummies goes in line with the findings of Cuaresma and Silgoner (2014). Moreover, if the municipality is located near the border of the European Union (EU dummy (-)), its economic activity growth rate is slower.

We see that the results by countries are quite different, for example, none of the factors works for Estonia in the medium run period which is represented in column 4 - even the nighttime light intensity per capita is insignificant and has a positive sign in the regression. The possible explanation for such results could be that the trend of convergence in Estonian municipalities does not exist. Because the panel regression shows the results of a slow convergence speed (significant at a 10% level), this might be the case of the Estonian municipalities. Thus, we decide to exclude Estonia from further analysis.

The results for Latvia (column 2) and Lithuania (column 3) differ as well – the conditional convergence coefficient for the Latvian sample is four times bigger compared to Lithuania. Such values go in line with the nighttime light intensity growth rate in the large cities shown on the graph previously – the highest negative trendline belongs to Latvia. Moreover, the results of these regression are different from the results in Table 4 and Table 5 due to the use of different factors for the regression, as well as the fact that this regression was checking the effects of the medium run, not the short run effect of each factor. At the same time, other countries do not experience such a significant drop. Moreover, due to the specifics of each country, the factors influence the growth rate of economic activity differently. For example, the significant factors for Latvia, such as the municipal budget revenue per capita, crime rate growth, coastal dummy and large city dummy, are insignificant in the case of Lithuanian municipalities. However, the EU border dummy and time to the capital city are significant in the case of Lithuania and are insignificant for the Latvian sample.

Overall, the results allow us to answer the third research question and partially confirm our third hypothesis regarding the factors influencing the growth rate

This table reports the cross-section regression using the data for local administrative units (LAU) in the Baltic States of 2011. $MLgrowth_{i,t}$ is the relative increase of the nighttime light intensity per capita from 2011 to 2017. $MLights_{i,t}$ is the initial level of nighttime light intensity per capita in 2011. $atWA_{i,t}$ is the fraction of population at the working age. $Budget_{i,t}$ is the municipal budget revenue per capita. $Coast_i$,is the coastal dummy. $LargeCity_i$ is a large city dummy. EU_i is the EU border dummy. $TimeCapital_i$ represents the time to the capital from the municipality. Standard errors are clustered both by municipality and year, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Variable	Latvia and Lithuania (1) $MLgrowth_{i,t}$	Latvia (2) $MLgrowth_{i,t}$	Lithuania (3) $MLgrowth_{i,t}$	Estonia (4) $MLgrowth_{i,t}$
$MLights_{i,}$	-2.028*** (0.442)	-2.506*** (0.593)	-0.688*** (0.245)	0.232 (0.155)
$atWA_i$	5.426* (2.862)	11.136* (5.823)	6.590*** (1.366)	0.119 (0.516)
$Budget_{i,}$	0.439*** (0.261)	0.952* (0.486)	Omitted due to insignificance	0.004 (0.002)
$Cgrowth_{i,}$	-0.642*** (0.150)	-0.693*** (0.168)	Omitted due to insignificance	Omitted due to data unavailability
$Coast_{i,}$	-0.396*** (0.122)	-0.333** (0.162)	Omitted due to insignificance	-0.096 (0.156)
$LargeCity_i$	-0.410* (0.150)	-0.676*** (0.213)	Omitted due to insignificance	-0.116 (0.179)
EU_i	Omitted due to insignificance	Omitted due to insignificance	-0.134* (0.087)	0.421 (0.344)
$TimeCapital_i$	Omitted due to insignificance	Omitted due to insignificance	0.001* (0.001)	0.003** (0.001)
Number of municipalities	179	119	60	79
Observations	179	119	60	79

Table 6. Conditional convergence in Baltic municipalities in the medium run (2011-2017). Created by the authors using data from NOAA (2019) and official statistics authorities.

To sum up the results of all types of regressions, we create a table with the list of significant factors specifying the regression type and sign. We conclude that out of our factor list created in the data section, the following factors significantly influence the economic activity growth rate in the municipalities either in panel or cross-section regression.

Variable	*Sign*	*Samples where it works*	*Regression type*	*In line with*
$MLights_{i,t}$	-	Baltics, Latvia, Lithuania, Estonia (partially)	Panel and cross-section	
$PGrowth_{i,t}$	-	All samples	Panel	Solow (1956) and Swan (1956)
$atWA_{i,t}$	+	Baltics, Latvia, Lithuania	Cross-section	Solow (1956) and Swan (1956)
$belowWA_{i,t}$	-	Baltics, Latvia, Estonia	Panel	Solow (1956) and Swan (1956)
$Budget_{i,t}$,	+	Baltics (partially), Latvia, Lithuania (partially)	Panel and cross-section	Barro (1991)
$BGrowth_{i,t}$,	+	All samples	Panel	Barro (1991)
$CGrowth_{i,t}$	-	Baltics, Latvia	Cross-section	Temple (2009)
$EUFunds_{i,t}$	+	Latvia	Panel	Temple (2009), Barro (1991)
$LargeCity_{i}$	-	Baltics, Latvia	Cross-section	Christ (2012)
$TimeCapital_{i}$	+	Lithuania, Estonia	Cross-section	Christ (2012)
EU_{i},	-	Lithuania	Cross-section	
$Coast_{i}$	-	Baltics, Latvia	Cross-section	Cuaresma and Silgoner (2014)

Table 7. Summary of the significant factors. Created by the authors.

5.3 Policy suggestions

The factors influencing the economic growth rate in the empirical analysis belong to each of the three groups mentioned in Section II. Some of the factors can be changed by a certain policy of the government, while others cannot.

One of the changeable factors is the time to reach the capital city which can be reduced by, for example, building faster roads. This would improve the connection between the distant municipalities where the economic activity is lower and the capital which, according to our results, would positively affect the economic growth rate. However, for some of the Estonian municipalities located on islands the traveller should firstly pass the water barrier, so apart from building faster roads the government can also increase the water transport frequency which would decrease the time to reach the capital.

The next group of factors where we attribute such the municipal budget per capita, its growth rate, the criminal cases per capita and the investments from the European Union funds, almost fully consists of the factors that can be changed by the policy. The only exception is the factor representing the criminal rate per capita as the human actions cannot be really controlled even if the police forces in the municipality are strengthened. Yet, the governments can influence how the investments from the European Union funds are distributed across the municipalities. The money can be transferred to the to the municipalities that lag behind others in terms of the economic activity which would boost the economic growth there.

Lastly, the demographic factor group consists of factors representing the population growth, the fraction of population at the working age and the fraction of population below the working age. One of the possible ways to change the population level and its structure in a certain municipality is incentivizing people through inviting people from abroad, especially Latvian migrants to return to their former municipalities. This approach would help to avoid harming the population structure in other municipalities. However, the government should consider only those projects which would payoff in the long term, otherwise this policy step would bring economic losses in the country's economy for economic growth boost in the municipality.

To sum up, to boost the economic growth in municipalities that lag behind others the governments might consider steps to reduce the time to reach the capital city, reallocate the investments from the EU funds and organize several projects to increase the population at the working age in municipalities that lag behind others.

5.4 Limitations

There are several limitations to the study. For example, there are limitations in the panel regression approach that are connected to the fixed effects. If the fixed-effect panel regression contains constant factors that do not change at all in the sample period, the model cannot determine the marginal effects of such factors and treats them as a part of the fixed effects. Thus, it determines only the total marginal effect of all fixed effects in the regression without showing the individual marginal effects of each constant factor separately.

Another important limitation is connected to the data. The administrative division by municipalities implies that the studied territory is not vast, and there are no borders. Thus, we acknowledge that some accuracy issues in the data might occur. For example, there might be a potential drawback in the population data when the inhabitant could be registered in one municipality but be economically active in another. Besides, we can check only observable factors which are publicly available while in reality the economic growth and conditional convergence could also be explained by the variables which are not observable at the municipal level. For example, these factors might include educational quality, fertility rate or the municipal budget divided by its GDP suggested by Barro (1991) or division by employment type suggested by LeSage and Fischer (2008).

VI. CONCLUSION

The paper demonstrates that the revolutionary approach of proxying the economic activity through nighttime light intensity is applicable for the Baltic countries as well, so the problem of lacking the economic activity data can be solved with our approach. In particular, it closely represents the economic activity level in NUTS-3 regions. Thus, we confirm our first hypothesis and provide an answer to the first research question – the regional economic activity level in the Baltics can be proxied using nighttime light intensity data. Consequently, the nighttime light intensity can be used to study economic activity patterns at the regional level. These conclusions contribute to the findings of Elvidge et al. (2007), Henderson et al. (2012) and Hu and Yao (2019) by showing that the approach of nighttime light intensity is applicable for the smaller territorial divisions such as NUTS-3 regions.

Another critical contribution this paper makes is related to the convergence studies in the Baltic municipalities. We find that the convergence patterns in the Baltic municipalities exist both in the short and medium run. Moreover, there is some evidence of short-term absolute beta convergence presence across all three Baltic countries. Additionally, the conditional beta convergence exists in the municipalities as well, so we can confirm our second hypothesis and answer our second research question – there is a beta-convergence pattern in the Baltics at the level of municipalities. Studying the beta convergence pattern in the municipalities contributes to the results of the studies by Alcidi et al. (2018) and Zuk et al. (2018) who study the convergence in Europe at a country and NUTS-3 level, including the Baltics. Comparing our findings with these two studies, we indicate that the convergence speed in the municipalities is slower compared to the NUTS-3 level regions or countries

Finally, the conditional convergence research shows that the part of the factors tested in this research is related to the economic activity growth in the Baltic municipalities. Thus, we can partially confirm our third hypothesis and answer the third research question by naming the factors that influence economic activity growth. The factors positively impacting the economic growth are the fraction of the population at the working age, municipal budget revenue per capita and its growth, the EU fund investments. The factors negatively influencing the economic growth rate are population growth, higher crime rate or its growth, the coastal dummy, EU dummy and a large city dummy. We contribute to the existing literature by finding that these factors also work at the municipal level and are one of the first who study the economic beta-convergence in the Baltic municipalities. Moreover, we outline that the governments might consider reducing the time to reach the capital city, increasing the working age population and reallocating the EU funds' investments across the municipalities to increase the economic growth in municipalities which lag begind others.

VII. REFERENCES

Alcidi, C., Ferrer, J. N., Di Salvo, M., Musmeci, R., Pilati, M. (2018). Income Convergence in the EU: A tale of two speeds. *CEPS paper.*

Bao, S. M., Chang, G. H., Sachs, J. D., and W. T. Woo. (2002). Geographic Factors and China's Regional Development under Market Reforms, 1978-1998. *China Economic Review*, *13*, 89-111.

Barro, R. (1991). Economic growth in a cross section of countries. *Quarterly Journal of Economics 106 (2)*, 407–443.

Chen, X. (2016). Addressing Measurement Error Bias in GDP with Nighttime Lights and an Application to Infant Mortality with Chinese County Data. *Sociological Methodology, Vol. 46*, 319-344.

Christ, J. P. (2012). Research Clustering, Income Disparities and the Growth of Regions in Europe. *Innovative Places in Europe*

Cuaresma, J. C., Silgoner M. (2014). Economic Growth and Inflation in Europe: A Tale of Two Thresholds. *Journal of Common Market Studies. Volume 52. Number 4.* pp. 843–860.

Dayal-Gulati, A., Husain, A. M. (2002). Centripetal Forces in China's Economic Takeoff. *IMF Staff Papers, Vol. 49, No. 3* pp. 364-394.

Demurger, S. (2001). Infrastructure Development and Economic Growth: An Explanation for Regional Disparities in China. *Journal of Comparative Economics, 29*, 95-117.

Donaldson, D., Storeygard, A. (2016). The View from Above: Applications of Satellite Data in Economics. *The Journal of Economic Perspectives Vol. 30, No. 4*

Doll, C., Jan-Peter Muller N. H., Morley, J.G. (2006). Mapping regional economic activity from night-time light satellite imagery. *Ecological Economics, Vol 57,* 75–92.

Easterly, W., and Levine, R. (1997). Africa's growth tragedy: policies and ethnic divisions. *The quarterly journal of economics*, *112*(4), 1203-1250.

Eicher, T. S., Papageorgiou, C., and Roehn, O. (2007). Unraveling the fortunes of the fortunate: an iterative Bayesian model averaging (IBMA) approach. *Journal of Macroeconomics*, *29*(3), 494-514.

Elvidge, D. C., Safran, J., Tuttle, B., Sutton, P., Cinzano, P., Pettit, D., Arvesen J., Small, C. (2007). Potential for global mapping of development via a nightsat mission. *GeoJournal. Vol. 69, No. ½*

Eurostat. (2019). Local Administrative Units (LAU). Retrieved from https://ec.europa.eu/eurostat/web/nuts/local-administrative-units

Galor, O. (1995). Convergence?: Inferences from Theoretical Models. *Conference Paper. Economic Journal, July 1996.*

Hannan, T. H. (1997). Market share inequality, the number of competitors, and the HHI: An examination of bank pricing. *Review of Industrial Organization*, *12*(1), 23-35.

Henderson, D. J., and Russell, R. R. (2005). Human Capital and Convergence: A Production-Frontier Approach. *International Economic Review*, *46*(4), 1167-1205.

Henderson, J. V., Storeygard A., Weil N. D.(2012). Measuring Economic Growth from Outer Space *American Economic Review, Vol. 102, No*. 2, pp. 994–1028.

Hodler, R., Raschky P.A. (2014). Regional Favortivism. *The Quarterly Journal of Economics*, *Vol. 129,* 995 - 1033

Hu, Y., Yao, J. (2019). Illuminating Economic Growth. *IMF working paper.*

Juessen, F. (2009). A distribution dynamics approach to regional GDP convergence in unified Germany. *Empirical Economics*, *2009*, *37 (3),* 627 - 652.

LeSage, J. P., and Fischer, M. M. (2008). Spatial growth regressions: model specification, estimation, and interpretation. *Spatial Economic Analysis*, *3*(3), 275-304.

Levine, R., and Renelt, D. (1992). A sensitivity analysis of cross-country growth regressions. *The American economic review*, 942-963.

Mankiw, N. G., Romer, D., and Weil, D. N. (1992). A contribution to the empirics of economic growth. *The quarterly journal of economics*, *107*(2), 407-437.

Michalopoulos, S., Papaioannou, E. (2013). Pre-Colonial Ethnic Institutions and Contemporary African Development. *Econometrica*, *81,* 113–152.

Rhoades, S. A. (1993). The Herfindahl-Hirschman Index. *Fed. Res. Bull.*, *79*, 188.

The National Oceanic and Atmospheric Administration. (2019). Nighttime lights data. Retrieved from https://www.ngdc.noaa.gov/eog/viirs/download_dnb_composites_iframe.html and https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html

Sirimaneetham, V., Temple, J. R. (2009). Macroeconomic stability and the distribution of growth rates. *The World Bank Economic Review, 23(3),* 443-479.

Solow, R. M. (1956). A contribution to the theory of economic growth. *The quarterly journal of economics,* 70(1), 65-94.

Südekum, J. (2003). Spatial economic disparities within the European Union: The evidence. *Agglomeration and Regional Unemployment Disparities.*

Swan, T. W. (1956). Economic growth and capital accumulation. *Economic Record*, 32(2), 334-361.

Temple, J. (1999). The new growth evidence. *Journal of economic Literature, 37(1),* 112-156.

Yang, C., Zhao, Z., Zhang, Z. (2017). Empirical Study of Regional Innovation Capability and Economic Convergence in China. *China's New Sources of Economic Growth.*

Zuk, P., Polgar, E. K., Savelin, L., del Hoyo, J. L. D., Konig, P. (2018). Real convergence in central, eastern and south-eastern Europe. *ECB Economic Bulletin, Issue 3 / 2018.*

VIII. APPENDICES

Appendix A. Google Earth Engine code for nighttime light data extraction

```
//Visualization settings
var dataset = ee.ImageCollection('NOAA/VIIRS/DNB/MONTHLY_V1/VCMSLCFG')
                  .filterBounds(geometry)
                  .filterDate('2019-01-01', '2020-01-01');
var nighttime = dataset.select('avg_rad');
var nighttimeVis = {min: 0.0, max: 20.0};

var mean_new = sorted.arrayReduce({
  reducer: ee.Reducer.mean(),
  axes: [0]
});
var nightlights_sorted = mean_new.arrayProject([0]).arrayFlatten([['avg_rad']]);
//importing boundaries for latvia
var latvia = latvia_regions
  .filter(ee.Filter.notNull(['CODE']))
  .reduceToImage({
    properties: ['CODE'],
    reducer: ee.Reducer.first()
});
//importing boundaries for lithuania
var lithuania = lithuania_regions
  .filter(ee.Filter.notNull(['FID']))
  .reduceToImage({
    properties: ['FID'],
    reducer: ee.Reducer.first()
});
//importing boundaries for estonia
var estonia = estonia_regions
  .filter(ee.Filter.notNull(['OKOOD2']))
  .reduceToImage({
    properties: ['OKOOD2'],
    reducer: ee.Reducer.first()
});
//combining nightlights and boundaries
var combination_latvia = nightlights_sorted.addBands(latvia);
var combination_lithuania = nightlights_sorted.addBands(lithuania);
var combination_estonia = nightlights_sorted.addBands(estonia);
//Collecting average nightlight by county for latvia
var means = combination_latvia.reduceRegion({
  reducer: ee.Reducer.sum().group({
    groupField: 1,
    groupName: 'CODE',
  }),
  geometry: latvia_regions.geometry(),
  scale: 1000,
  maxPixels: 1e8
});
```

```
//Collecting average nightlight by county for lithuania
var means1 = combination_lithuania.reduceRegion({
  reducer: ee.Reducer.sum().group({
    groupField: 1,
    groupName: 'FID',
  }),
  geometry: lithuania_regions.geometry(),
  scale: 1000,
  maxPixels: 1e8
});
//Collecting average nightlight by county for estonia
var means2 = combination_estonia.reduceRegion({
  reducer: ee.Reducer.sum().group({
    groupField: 1,
    groupName: 'OKOOD2',
  }),
  geometry: estonia_regions.geometry(),
  scale: 1000,
  maxPixels: 1e8
});
//Merging dictionaries into list
var final = means.get('groups');
var final1 = means1.get('groups');
var final2 = means2.get('groups');
var final_final= ee.List(final).cat(final1).cat(final2);
//Exporting
var dict = {dict: final_final};
var feature = ee.Feature(null, dict);
var featureCollection = ee.FeatureCollection([feature]);
print (featureCollection);
Export.table.toDrive({
  collection: featureCollection,
  description: 'Test',
  fileFormat: 'CSV'
});
```

Figure A.1. Google Earth Engine code for the nighttime light intensity data extraction

Appendix B. Descriptive statistics

Descriptive statistics

Variable	*Observations*	*Mean*	*Standard deviation*	*Min*	*Max*
$RegionalGDP_{i,t}$	175	9.522	0.447	8.205	10.491
$RLights_{i,t}$	175	9.837	1.181	7.782	12.259
$RLightsAVG_{i,t}$	175	0.424	1.196	-1.399	2.925
$MLights_{i,t}$	1866	0.165	0.246	0.000	2.991
$MLightsAVG_{i,t}$	1866	0.189	1.597	-4.605	4.084
$RElectricity_{i,t}$	35	20.700	0.664	20.255	22.015
$MLGrowth_{i,t}$	1866	0.053	0.294	-1.756	1.548
$Population_{i,t}$	1866	9.330	1.145	4.043	13.410
$PGrowth_{i,t}$	1866	-0.011	0.027	-0.301	0.360
$abWA_{i,t}$	1863	0.202	0.361	0.008	0.286
$Density_{i,t}$	1866	153.217	404.505	0.066	2676.401
$Budget_{i,t}$,	1787	1.459	4.795	0.016	98.284
$BGrowth_{i,t}$,	1529	0.319	0.451	-0.424	1.357
$Investments_{i,t}$	1313	696.070	2031.279	0.000	20586
$Crime_{i,t}$,	1313	0.018	0.007	0.004	0.060
$CGrowth_{i,t}$	1250	-0.044	0.262	-1.592	1.408
EUFundsi,t,	833	5.819	1.387	-0.418	8.079
$LargeCity_i$	1866	0.100	0.300	0.000	1.000
$Region_i$	258	10.593	8.799	0.000	30.000
$DistLargeCity_i$	258	105.837	65.351	1.000	216.000
$TimeLargeCity_i$	258	38.531	19.666	1.000	80.000
$DistCapital_i$	258	87.632	56.384	1.000	194.000
$TimeCapital_i$	258	74.640	44.205	1.000	149.000
EU_i,	258	0.109	0.312	0.000	1.000
$Coast_i$	258	0.178	0.384	0.000	1.000

Table B.1. Descriptive statistics for the applied factors

Appendix C. Used variables and respective sources

Variable	*Source*
$RegionalGDP_{i,t}$	Central statistical databases
$RLights_{i,t}$	NOAA
$RLightsAVG_{i,t}$	NOAA
$MLights_{i,t}$	NOAA
$MLightsAVG_{i,t}$	NOAA
$RElectricity_{i,t}$	Central statistical databases
$MLGrowth_{i,t}$	Calculated
$Population_{i,t}$	Central statistical databases
$PGrowth_{i,t}$	Calculated
$abWA_{i,t}$	Central statistical databases
$Density_{i,t}$	Central statistical databases
$Budget_{i,t}$,	Central statistical databases
$BGrowth_{i,t}$,	Calculated
Investments	Central statistical databases
$Crime_{i,t}$,	Central statistical databases
$CGrowth_{i,t}$	Calculated
$EUFunds_{i,t}$	Central statistical databases
$LargeCity_{i}$	Calculated
$Region_{i}$	Calculated
$DistLargeCity_{i}$	Google Maps
$TimeLargeCity_{i}$	Google Maps
$DistCapital_{i}$	Google Maps
$TimeCapital_{i}$	Google Maps
EU_{i},	Google Maps
$Coast_{i}$	Google Maps

Table C.1. Sources of the variables

Appendix D. Robustness check

Table 4

Absolute beta-convergence in Baltic municipalities without adding 0.01

This table reports panel regression using annual data for local administrative units (LAU) in the Baltic States during 2011-2018. $MLgrowth_{i,t}$ is the relative increase of the log of total municipal GDP. Standard errors are clustered both by municipality and year, and t-statistics are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Variable	All countries (1) *MLgrowth*	Latvia (2) *MLgrowth*	Lithuania (3) *MLgrowth*	Estonia (4) *MLgrowth*
$MLights_{i,t}$	-0.150*** (0.049)	-0.832*** (0.160)	-1.177*** (0.171)	-0.167*** (0.056)
Number of municipalities	258	119	60	79
Observations	1,866	833	480	553
Fixed effects	Yes	Yes	Yes	Yes

Table D.1. Robustness check for the approach of adding 0.01 to the nighttime light intensity values

Appendix E. Regional GDP and Nighttime lights comparison

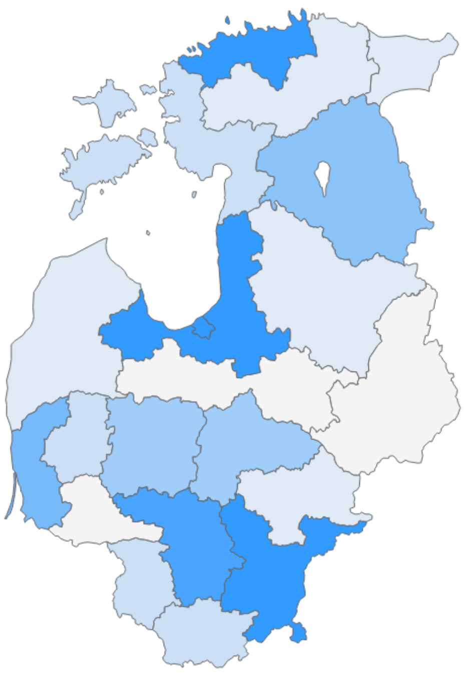

Figure E.1. Nighttime lights in Latvia in 2010. Created by the authors using data from NOAA (2019).

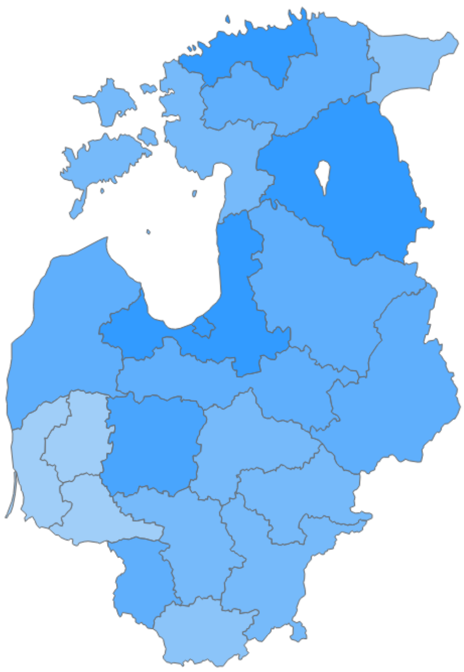

Figure E.2. Nighttime lights in Latvia in 2010. Created by the authors using data from NOAA (2019).