

Economic Performance of Nigerian States Through the Lens of Satellite-Recorded Nighttime Light Data

Kingsley Success Ikani

kingsleysuccessikani@gmail.com

University of Economics in Katowice <https://orcid.org/0000-0001-7499-6136>

Research Article

Keywords: Econometrics, spatio analysis, Economic performance, Satellite-Recorded Nighttime light, convergence analysis, regional economics

Posted Date: October 5th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11244500/v1>

License:   This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: The authors declare no competing interests.

Economic Performance of Nigerian States Through the Lens of Satellite-Recorded Nighttime Light Data

Kingsley Success IKANI

University of Economics in Katowice

Kingsley.ikani@edu.uekat.pl

ORCID: 0000-0001-7499-6136

Abstract

This study develops and applies a novel methodology for estimating state-level Gross Domestic Product (GDP) in Nigeria using satellite-recorded Nighttime Lights (NTL) data. Motivated by the absence of comprehensive subnational GDP statistics, the research integrates remote sensing and econometric modeling to provide spatially detailed insights into Nigeria's economic dynamics. NTL intensity data, obtained from the Earth Observation Group, are combined with fixed effects panel regressions, β - and σ -convergence tests, and elasticity estimation to examine the relationship between luminosity and economic activity. Results reveal a strong, positive, and statistically significant correlation between NTL and GDP, with elasticity estimates of approximately 0.096 for growth rates and 0.207 for levels, and R^2 values up to 0.95 under fixed effects. The NTL-based GDP estimates broadly reproduce official state rankings and national aggregates, though systematic underestimation occurs in agriculturally oriented states and overestimation in highly illuminated but lower-output regions. Convergence analyses indicate both absolute and conditional convergence in per capita GDP, highlighting gradual regional equalization with structural heterogeneity. Findings confirm that while NTL is a valuable and cost-effective proxy for economic activity, it is not a perfect substitute - particularly for agriculture, informal sectors, and offshore production. The study recommends integrating NTL with other complementary indicators, developing state-specific adjustment factors and institutionalizing satellite-based monitoring within national statistical systems to enhance subnational economic tracking and evidence-based policymaking. Overall, the research demonstrates the practical viability of remote sensing as a tool for assessing and understanding regional economic performance in data-scarce environments.

1.0. Introduction

In recent years, the integration of satellite technology has become a powerful tool in elucidating various facets of human activity, especially in the context of economic research. One such innovative approach involves the use of satellite-recorded nighttime light data as a substitute indicator for economic performance. This approach has proven particularly insightful in examining the economic dynamics of nations and regions, providing a unique lens through which to understand development patterns and disparities (Addison & Stewart, 2015). In Nigeria, while annual GDP data is readily accessible at the national level, it remains unavailable for individual states within the country. The National Bureau of Statistics has been actively working towards compiling GDP data for all 36 states since 2013, yet they have only managed to do so for 22 states thus far (Nigerian NBS, 2019). Relying solely on the publication of annual GDP figures at the national level proves inadequate for facilitating efficient and informed policy-making and decision-making processes. Moreover, it fails to provide a comprehensive overview of the economic landscape at the state level. Consequently, there is a pressing need to estimate GDP figures at the state level in order to obtain a more holistic understanding of the economy across the nation. The compilation of states' GDP data holds significant importance and utility across multiple domains. Primarily, it serves as crucial information supporting evidence-based policymaking. Additionally, it aids in pinpointing the primary catalysts of economic expansion within individual states and evaluating their economic performance. Moreover, by elucidating the economic structure of each state, it enables the determination of their respective contributions to the national output.

Nigeria, as the most populous country in Africa and a significant player in the global economy, presents a multifaceted landscape of economic activity and development. However, the diverse and often uneven economic performance across its states poses a critical challenge for policymakers, researchers and stakeholders seeking to understand and address regional disparities (Aka, 2000). Traditional economic metrics, such as gross domestic product (GDP) and employment rates provide valuable insights but often fail to capture the intricacies of economic activities at a subnational level. Against this backdrop, Satellite-recorded nighttime

light data emerges as a groundbreaking alternative, offering a dynamic and real-time measure of economic vibrancy (Sutton et al., 2007; Hu & Yao, 2022). Nighttime lights are a direct result of human activity, capturing the illumination emanating from urban centres, industrial zones and commercial areas. The intensity and spatial distribution of these lights serve as an indirect but reliable proxy for economic productivity, urbanization and overall economic well-being (Lopez-Ruiz et al., 2019; Bluhm & McCord, 2022; Perez-Sindin et al., 2021). By harnessing this data, we can gain a comprehensive understanding of economic trends, identify growth patterns and pinpoint regions requiring targeted interventions.

Nigerian states, each with its unique socio-economic characteristics and challenges provide an ideal canvas for the application of this methodology. The vast expanse of the country encompassing bustling metropolises, agrarian landscapes and resource-rich regions, offers a rich tapestry of economic diversity. Leveraging satellite-recorded nighttime light data enables a granular examination of economic activities, allowing for the identification of disparities and growth trajectories across the states.

This research aims to contribute to the existing body of knowledge on the economic dynamics of Nigerian states by combining traditional economic analyses with cutting-edge satellite technology. By doing so, we seek to address crucial questions regarding the following:

- 1) How can satellite-recorded Nighttime lights data be effectively utilized to develop a methodology for estimating the regional GDP in Nigerian States?
- 2) To what extent does nighttime lights intensity correlate with economic activities (GDP) and how can this correlation be leveraged to improve the accuracy of GDP estimates for Nigerian States?
- 3) How do the estimated State-level GDP compare with existing official statistics and what insights can be drawn regarding the reliability and accuracy of the proposed methodology?
- 4) To what extent the estimates reveal convergence patterns for economic activity of Nigerian states?
- 5) is satellite-recorded Nighttime lights a perfect proxy for measuring economic activity in Nigeria.
- 6) What are the potential implications of the research findings for policymakers and practitioners involved in economic planning and development at the State level in Nigeria?

These research questions explore how satellite-recorded nighttime lights data can be utilized to develop a methodology for estimating regional GDP in Nigerian states. They examine the correlation between nighttime light intensity and economic activities (GDP), aiming to leverage this relationship to enhance the accuracy of GDP estimates. The study compares these estimates with existing official statistics to evaluate the reliability and accuracy of the proposed methodology. It also investigates whether the estimates reveal convergence

patterns in the economic activity of Nigerian states. Finally, the research considers the implications of these findings for policymakers and practitioners involved in economic planning and development at the state level in Nigeria. These questions would be answered by disaggregating the Nigerian country-level GDP data with nighttime lights (collected from Earth Observation group) using Fernandez random walk variation of Chow-Lin disaggregation procedures, examining the correlation between the intensity of nighttime lights and economic indicators such as the disaggregated states GDP and examining the economic convergence of the Nigerian states using the estimated GDP data.

The main research problem lies in the lack of subnational GDP data and the lack of comprehensive studies that leverage on Satellite-recorded nighttime light data to analyze the economic dynamics of individual states in Nigeria, hindering the identification of precise factors influencing economic performance and potential implications for policy formulation. Hence, this research fills this knowledge gap. As we embark on the exploration of Nigeria's economic landscape through the lens of nighttime light data, we anticipate uncovering insights that transcend conventional boundaries, fostering a deeper understanding of the nation's economic intricacies and providing valuable guidance for future policy formulation.

The goal of this research is to assess the economic performance of Nigerian states using satellite-recorded nighttime light data and our motivation stems from the quest to gain insights into the spatial and temporal dynamics of economic growth and urbanisation across Nigeria, with the intention to enhance our understanding of regional development disparities and regional economic health, in order to inform policymakers about areas needing targeted interventions and resources.

2.0. Literature Review on Time Series Disaggregation

Over the decades, economists have developed various methods to disaggregate macroeconomic variables such as GDP from lower-frequency data. In 1964, Lisman and Sandee introduced an early endeavour to extrapolate quarterly estimates from annual data. Their approach involved constructing a quarterly time series by scrutinizing the absolute changes in macroeconomic variables between consecutive years, dissecting seasonal fluctuations within a given year, and applying a transition matrix for linear interpolation. However, this technique necessitates access to datasets recorded annually. In 1967, Boot, Feibes, and Lisman (BFL) proposed a similar methodology wherein quarterly observations were derived by minimizing the sum of squared discrepancies between adjacent quarters, while simultaneously imposing constraints on the sum of quarterly values and the observed annual total. Denton's study in 1971 followed a similar path, integrating supplementary auxiliary variables of identical frequency as the target variable. These methodologies underwent further

refinement towards dynamic approaches grounded in ARIMA models (Wei & Stram, 1986, 1990; Guerrero & Martínez, 1995) or factor models (Angelini et al., 2006; Marcellino, 2007). Such advancements facilitated the generation of higher-frequency time series observations from primary series data, providing a direct linkage between annual growth information and estimated patterns of quarterly fluctuations, which are primarily influenced by seasonal variations or numerical interpolation. These techniques find common usage in scenarios where additional estimations of missing observations are necessary.

The second category of methodologies involves techniques incorporating supplementary explanatory variables sharing the same frequency as the target variable (Chen, 2007). This category emerged with the pioneering work of Chow and Lin in 1971, wherein they established the best linear unbiased estimator and its covariance matrix for values sought at a monthly frequency (Infante, 2017; Bettendorf & Bursian, 2017). Their analysis relied on a regression model, with the dependent variable observed quarterly, while explanatory variables with a higher (monthly) frequency were available. Chow and Lin emphasized that the vector of explanatory variables could include leading or lagging variables relative to the target variable, as well as trend or binary variables. Their methodology laid the groundwork for the widely adopted data interpolation method, with subsequent methods often being variations thereof. For example, Rossi in 1982 introduced the necessity of equality between the aggregate and the sum of data available at a higher frequency (e.g., the quarterly total and the sum of monthly values comprising it). Fernandez in 1981 and Littermann in 1983 introduced more sophisticated stochastic structures, positing temporal dependencies among error terms.

Beyond statistical interpolation, the integration of satellite technology has emerged as a powerful tool in elucidating various facets of human activity, especially in economic research. One such innovative approach involves the use of satellite-recorded nighttime light (NTL) data as a substitute indicator for economic performance (Addison & Stewart, 2015). Historically, human activity ceased at sunset, but the advent of electricity extended productivity into the night, influencing economic growth. Nighttime radiance, captured by satellites, has been shown to correlate strongly with GDP, offering an alternative estimation method where official data is missing or unreliable (Monteiro et al., 2018; Hu & Yao, 2019; Cuaresma et al., 2020). Studies have demonstrated that NTL data can evaluate GDP (Hu & Yao, 2019), assess the economic effects of shocks such as natural disasters or wars (Beyer et al., 2018), and represent seasonal variations in GDP and Gross State Domestic Product (GSDP) in African countries such as Kenya and Rwanda (Bundervoet et al., 2015; Hamman & Phiri, 2022).

In the recent studies, Liu et al. (2021) proposed a deep learning framework that uses nighttime light intensity as a proxy for economic activity to estimate county-level Gross Domestic Product (GDP) across mainland China. Rather than relying solely on traditional

administrative statistics, the study integrates daytime satellite imagery with nighttime light data through a transfer learning approach, allowing the model to learn meaningful socioeconomic features from remotely sensed images. An attention-augmented VGG-16 convolutional neural network (CNN) was employed to improve feature extraction by emphasizing economically relevant regions in the imagery. After feature extraction, dimensionality reduction and statistical aggregation techniques were applied before using a regression model to estimate county-level GDP. The proposed model achieved an R^2 value of 0.71 when predicting 2018 GDP using 2017 satellite data, demonstrating strong predictive performance. Additionally, gradient visualization techniques showed that the CNN focused on urban infrastructure, transportation networks, and developed areas that are closely associated with economic productivity. The authors concluded that combining daytime and nighttime satellite imagery with attention-based deep learning provides a scalable and cost-effective alternative to conventional GDP surveys, particularly for producing fine-grained economic estimates in regions where official statistics are limited or delayed.

Furthermore, Yue et al. (2026) proposed an Earth Embedding (EMB) framework that leverages satellite embeddings to estimate economic activity at a global scale. The study uses the Google Satellite Embedding Dataset (GSED) to extract high-dimensional representations from optical and radar satellite imagery and aligns these embeddings with nighttime light (NTL) intensity using a neural network. The resulting "income-aware" feature space is then used to predict GDP levels and economic growth across countries. Compared with traditional NTL-based models, the EMB approach achieved lower mean squared error in GDP estimation, while combining EMB and NTL data produced the highest overall prediction accuracy. The authors also found that the EMB model performs particularly well in countries with limited statistical capacity and in high-income economies, demonstrating its potential as a scalable and globally consistent tool for monitoring economic development and validating official economic statistics. In our study, we will utilize Fernandez Random walk model, a variation of Chow-Lin disaggregation methods for GDP data. While the reviewed and existing literature has applied nighttime lights (NTL) data to examine various aspects of economic activity, none of the studies has applied this approach to disaggregate Nigeria's GDP at the state level and test for convergence among the estimated state GDPs. This study fills this gap in the literature by using NTL data to estimate state-level GDP and subsequently examining the convergence patterns across Nigerian states.

Table 1: Related Statistical and Empirical Literature.

Author(s)	Countries	Years	Methods	Aim
-----------	-----------	-------	---------	-----

Hamman & Phiri (2022)	49 African countries	1992-2012	PMG	To test if night light luminosity data can be used as an alternative measure of GDP
Bundervoet et al., (2015)	47 district in Kenya, 30 districts in Rwanda	2013	Regression	To estimate subnational economic growth using NTL
Suleiman (2024)	Egypt	1992-2021	Regression	To estimate subnational GDP using NTL
Mveyange (2015)	42 African countries	2000-2012	Regression	To estimate regional income inequality using NTL
Coetzee & Kleynhans (2021)	South Africa	1992-2019	ARDL	To estimate regional GDP using NTL

Source: Compiled by the author.

Table 1 summarizes selected statistical and empirical studies that have applied nighttime light (NTL) data to the measurement and analysis of economic activity, particularly in contexts where conventional economic statistics may be limited. The reviewed studies cover several African countries and regions, including Kenya, Rwanda, Egypt, and South Africa, over different periods between 1992 and 2021. Various econometric techniques, including regression analysis, the Pooled Mean Group (PMG) approach, and the Autoregressive Distributed Lag (ARDL) model, were employed to examine the relationship between nighttime luminosity and economic indicators.

Overall, the literature demonstrates the growing application of NTL data as an alternative or complementary measure of economic activity. While Hamman and Phiri (2022) examined its suitability as an alternative measure of GDP across African countries, Bundervoet et al. (2015) and Suleiman (2024) focused on estimating subnational economic growth and GDP. Mveyange (2015) extended its application to the measurement of regional income inequality, while Coetzee and Kleynhans (2021) examined regional GDP using NTL data in South Africa. Collectively, these studies demonstrate the usefulness of nighttime light data for analysing GDP, economic growth, and regional inequality at both national and subnational levels.

2.1. Theoretical and Empirical Literature on Economic Convergence

The concept of economic convergence is rooted in the neoclassical growth framework of Solow and Swan (1956), which predicts that, under comparable structural conditions, economies with lower initial levels of capital and income may grow faster because of diminishing returns to capital. Subsequent empirical literature distinguishes between absolute β -convergence, where economies are assumed to converge toward a common steady state, and conditional β -convergence, where steady states differ according to structural characteristics such as savings, population growth and human capital (Barro & Sala-i-Martin, 1992; Mankiw et al., 1992; Ben-David, 1996). σ -convergence, by contrast, concerns reductions in the dispersion of income or other economic indicators over time, while convergence-club approaches allow groups of economies to follow different convergence paths (Baumol, 1986; Galor, 1996; Quah, 1993, 1996). Thus, β -convergence does not necessarily imply σ -convergence, since poorer economies may grow faster without producing a sustained decline in overall dispersion. More recently, convergence analysis has also been extended to structural indicators such as sectoral output and employment shares (Alemu et al., 2025; Glodowska, 2015; Young et al., 2008).

Empirically, conditional β -convergence is frequently examined using panel-data models that account for unobserved heterogeneity. Because dynamic panel models containing lagged dependent variables can be affected by Nickell bias and endogeneity (Nickell, 1981), the literature has employed fixed-effects and GMM approaches, including difference and system GMM (Arellano & Bond, 1991; Arellano & Bover, 1995; Blundell & Bond, 1998; Islam, 1995; Garang & Erkekoğlu, 2021).

Evidence on economic convergence in Africa remains mixed. Wane (2004) finds evidence that lower-income WAEMU economies converge toward higher-income members when economic policies are similar, while Wahiba (2015) also investigates conditional convergence in WAEMU using within and system-GMM estimators (Wane, 2004; Wahiba,

2015). Baafi (2018) examines income convergence between Sub-Saharan African (SSA) and high-income economies using dynamic panel methods and emphasizes the role of international trade, while Huffman and Huffman (2018) report evidence of conditional convergence among SSA economies over 1990-2015 (Baafi, 2018; Huffman & Huffman, 2018). In contrast, Kumo (2011) finds no evidence of absolute β -, σ -, or conditional β -convergence in real per capita GDP among SADC economies during 1992-2009, while Djennas and Belkacem (2014), examining 52 African countries over 1980-2011, report only very weak evidence of β -, σ -, and conditional β -convergence (Kumo, 2011; Djennas & Belkacem, 2014). Other studies similarly question the existence of broad-based convergence across African economies (Dufrénot et al., 2009, 2012; Aboagye & Turkson, 2013).

Building on these literatures, this study examines both unconditional and conditional β - and σ -convergence across Nigerian states. Conditional β -convergence is estimated using a fixed-effects panel model with a lagged dependent variable, with Driscoll–Kraay standard errors employed to provide robustness to heteroskedasticity, serial correlation and cross-sectional dependence. By focusing on Nigerian states and using estimated state GDP data where comprehensive publicly available state-level GDP data are limited, the study extends the predominantly cross-country African convergence literature to the subnational Nigerian context.

3.0. Research Methodology

The empirical strategy in this study combines advanced temporal disaggregation techniques with satellite-derived proxies for economic activity to construct and analyse a long-run panel of Nigerian state-level GDP. The starting point is the application of the Fernández random walk model (Fernández, 1981), a variation of the Chow-Lin method (Chow & Lin, 1971), to disaggregate annual national GDP figures into consistent state-level estimates. The Fernández model is particularly well suited for situations in which the related series exhibits high persistence, as it preserves the temporal dynamics of the indicator variable while satisfying the aggregation constraint. This approach allows for the generation of internally consistent subnational GDP estimates in contexts where official data are either incomplete or unavailable. The estimation process draws upon three main data sources. Nominal national GDP figures for Nigeria are obtained from the Nigerian National Bureau of Statistics.

3.1. Chow-Lin Regression Model-Based Disaggregation Approach

In 1971, Chow and Lin worked out a least-square optimal solution on the basis that a linear regression model involving the national account variable y and one or more related quarterly indicators X can be estimated using the annual data for national account variable and the annualized quarterly data for the indicator(s).

Let's consider that we have an annual series (GDP) spanning N years, which we aim to disaggregate into state GDP series. These state GDP series are associated with the k indicator (nighttime light) series. In this scenario, the relationship between the state GDP series (to be estimated through disaggregation) and the nighttime light indicator series can be expressed as follows:

$$y = X\beta + u, \quad (1)$$

where y is the GDP for the states i , to be estimated at time t , X is the nighttime light indicator for the states i , at time t , β is the coefficient of the indicator series and u is the stochastic disturbances with mean $E(u) = 0$ and variance, $E(uu') = V$, where V is a $(n \times n)$ matrix, $n = 1, \dots, i$. Since the disaggregated model (1) at the state level is not directly observable and cannot be estimated. Then (1) has to be transformed into a yearly model, which is observable. This transformation can be done by pre-multiplying the model (1) by the $(N \times n)$ aggregation matrix D (equivalent to national yearly GDP at time t , $GDP_t = c' \otimes I_N$, where c is a transposed of an identity matrix, $\otimes$ is the Kronecker product and $I_N = GDP_t$). The aggregated regression model becomes

$$y_0 = X_0\beta + u_0, \quad (2)$$

where $y_0 = Dy = yGDP_t$, $X_0 = DX = XGDP_t$ (a matrix), $u_0 = Du$ is the aggregated disturbance error, which has the mean of $E(u_0) = E(Du) = DE(u) = 0$ and covariance matrix, $E(u_0u_0') = E(Duu'D') = DVD' = V_0$. Model (2) is observable provided y_0, X_0 and u_0 are known. It is noteworthy to say that the aggregated model (2) only affects the error process, while β describes the parameters that characterise the linear relationship between the dependent and independent variables. Alternatively, in a simpler way, we can substitute equation (1) in the yearly annual additivity constraint below

$$Y = Dy, \quad (3)$$

which gives $Y = DX\beta + Du$, this is the same as equation (2). (3) is the observed national annual GDP series in relation to the states annual GDP series.

3.2. Estimation Procedure

In 1971, Chow and Lin derive the unbiased estimator $\hat{y}$ of y that is subject to the aggregation constraint of (2). Let assume V_0 is known, meaning V is also known, for the unbiased estimator of $\hat{y}$, then it is expected that the weighted sum of squared residuals (SSR) $= (\hat{y} - y)'V^{-1}(\hat{y} - y)$ should be minimum, provided that

$$D\hat{y} = y_0 \quad (4)$$

Assuming that a linear unbiased estimator $\hat{y}$ of y satisfies for some matrix H , then according model (4), we have:

$$\hat{y} = Hy_0 = H(X_0\beta + u_0) \quad (5)$$

The expectation of the estimation error becomes $E(\hat{y} - y) = E[H(X_0\beta + u_0) - (X\beta + u)]$, which implies that

$$(HDX - X)\beta = (Hy_0 - X)\beta. \quad (5b)$$

For the unbiased estimation, the expected error must be minimum, that is $E(\hat{y} - y) = 0$, for this condition to be fulfilled, (6) and (7) must be satisfied:

$$Hy_0 - X = 0, \quad (6)$$

$$\hat{y} - y = Hu_0 - u, \quad (7)$$

with the covariance matrix $\text{Cov}(\hat{y} - y) = E[(\hat{y} - y)(\hat{y} - y)'] = E[(Hu_0 - u)(Hu_0 - u)']$, which implies that

$$\text{Cov}(\hat{y} - y) = HV_0H' - HVD' - VD'H' + V \quad (8)$$

Since $E(uu_0') = E[(y - X\beta)(y_0 - X_0\beta)'] = E[(y - X\beta)(Dy - DX\beta)' = VD'$,

by minimizing equation (8) with respect to H subject to (6), we have the solution for H as follows: $H = X(X_0'V^{-1}_0X_0)^{-1}X_0V^{-1}_0 + (VD'V^{-1}_0)[1 - X_0(X_0'V^{-1}_0X_0)^{-1}X_0'V^{-1}_0]$, then the unbiased minimum variance estimator $\hat{y}$ is

$$\hat{y} = Hy_0 = X\hat{\beta} + (VD'V^{-1}_0)\hat{u}_0, \quad (9)$$

where

$$\hat{\beta} = (X_0'V^{-1}_0X_0)^{-1}X_0'V^{-1}_0y_0, \quad (10)$$

$\hat{u}_0 = [1 - X_0(X_0'V^{-1}_0X_0)^{-1}X_0'V^{-1}_0]$, again, multiplying (9) by D gives $D\hat{y} = DX\hat{\beta} + D(VD'V^{-1}_0)\hat{u}_0 = X_0\hat{\beta} + u_0 = y_0$, which meet the condition of equation (4). The estimator $\hat{y}$ of y is

$$\hat{y} = X\hat{\beta} + (VD'V^{-1}_0)\hat{u}_0. \quad (11)$$

The first term on right hand side of equation (11) is the predicted state GDP y based on the observed related indicator (State nighttime light data) and $\hat{\beta}$ is the estimate from annual national GDP from equation (10), whereas the second term is the allocation of the annual residuals $\hat{u}_0$ to states such that the annual sum of the interpolated values equal the observed value y_0 .

Since the covariance matrix V is not known and is the major drawback of Chow-lin procedure of 1971, in order to estimate the covariance matrix V , Chow-Lin proposed two assumptions as follows:

1. The first is that the disturbances are not serially correlated, each with variance σ^2 , then $V = \sigma^2I$ and that

2. The disturbances u follow the autoregressive model of first order, AR(1) as

$$u_t = \delta u_{t-1} + \varepsilon_t, |\delta| < 1 \forall t, \varepsilon \sim i.i.d(0, \sigma_\varepsilon^2) \text{ and } E(\varepsilon_i, \varepsilon_j) = 0, i \neq j.$$

Under the first assumption, $\hat{\beta}$ reduces to the OLS estimator, $\hat{\beta} = (X'_0 X_0)^{-1} X'_0 y_0$ and under the second assumption, V takes the form

$$V = \frac{\sigma_\varepsilon^2}{1-\delta^2} \begin{bmatrix} 1 & \delta & \delta^2 & \dots & \delta^{n-1} \\ \delta & 1 & \delta^2 & \dots & \delta^{n-2} \\ \delta^2 & \delta & 1 & \dots & \delta^{n-3} \\ \dots & \dots & \dots & \dots & \dots \\ \delta^{n-1} & \delta^{n-2} & \dots & \dots & 1 \end{bmatrix} \quad (12)$$

δ is unknown and has to be estimated but there is no convenient way to estimate it. However, Chow-Lin suggested using the following polynomial to estimate it.

$$\hat{\delta}_a = \frac{\delta(\delta+1)(\delta^2+1)^2}{2(\delta^2+\delta+2)}, \quad (13)$$

where, $\hat{\delta}_a$ is the estimated first order autocorrelation coefficient from the OLS residuals of the annual regression model in (5). The equation (5b) is derived by using the relationship that δ_a is equal to the ratio of the diagonal element to the diagonal element of the matrix $V_0 = DVD'$. Under the assumption that both δ_a and δ are positive, the equation (13) has only one positive real root which is an estimate of δ . If it is assumed that the aggregated disturbances term u follow the normal distribution as, $u \sim N(0, V)$, then δ , β and σ_ε^2 can be estimated through maximization of the log likelihood function. To estimate δ , we used R programming Language, where a set of values between -1 and 1 is assigned to δ and then V , $\hat{\beta}$ and σ_ε^2 are determined by choosing the value which maximizes the log function.

3.3. Fernandez Disaggregation Methods (Random Walk Model Approach)

The assumption that there is no serial correlation in the residuals of disaggregated estimates is generally not supported by empirical evidence. To address the issue of serial correlation in the disaggregated estimates using the Chow and Lin approach, two static variants have been proposed (Islam, 2009). The first is the random walk model developed by Fernandez (1981), and the second is the random walk-Markov model introduced by Litterman (1983). In this study, the Fernandez technique will be utilized.

Fernandez contends that economic time series data typically consist of both a trend and a cyclical component. He recommends transforming the series to remove the trend before estimation. He employs the standard Chow-Lin regression model to estimate $\hat{\beta}$ and $\hat{y}$, assuming that the residuals in the disaggregated model follow a random walk process as follows:

$$u_t = u_{t-1} + \varepsilon_t, t = 1, 2, \dots, n, \quad (14)$$

where the white noise $\varepsilon_t \sim N(0, \sigma^2)$ given that $u_0 = 0$. This approach allows to simplify the computation, the covariance matrices are: $\text{Cov}(\varepsilon_t, \varepsilon_j) = \sigma^2, \min(t, j), t \neq j, t, j = 1, 2, \dots, n$

Which means $E(uu') = V = \sigma^2(\Delta'_{1,n}\Delta_{1,n})^{-1}$ and

$$V_0 = DVD' = \sigma^2 D(\Delta'_{1,n} \Delta_{1,n})^{-1} D', \quad (15)$$

where $\Delta_{1,n}$ is the $(n \times n)$ matrix performing (approximate) first differences as

$$\Delta_{1,n} = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 & 0 \\ -1 & 1 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & -1 & 1 \end{bmatrix},$$

substituting equation (15) in (9) and (10), we have as follows:

$$\begin{aligned} \hat{y} &= X\hat{\beta} + (\Delta'_{1,n} \Delta_{1,n})^{-1} D' [D(\Delta'_{1,n} \Delta_{1,n})^{-1} D']^{-1} \hat{u}_0, \text{ and} \\ \hat{\beta} &= \langle X'_0 [D(\Delta'_{1,n} \Delta_{1,n})^{-1}] X_0 \rangle^{-1} X'_0 [D(\Delta'_{1,n} \Delta_{1,n})^{-1} D']^{-1} y_0. \end{aligned}$$

3.4. Relationship Between GDP Growth Rates and NTL Intensity Growth Rates

Various models have been used to estimate GDP using nighttime light data, including linear regression, exponential models, and sophisticated artificial neural network models. Among these, the regression model is notable for its accuracy and ease of implementation. Consequently, this study employs the following regression models to demonstrate the correlation between GDP growth rates and nighttime light intensity growth rates.

a. First difference (growth) linear regression model specification, as follows:

$$\Delta \ln(GSDP_{s,t}) = \xi_t + \gamma \Delta \ln(NTL_{s,t}) + u_{s,t}, \quad (16)$$

where $\Delta \ln(GSDP_{s,t})$ is the change of the natural logarithm of GSDP for states s in year t measured in constant prices. $\Delta \ln(NTL_{intensity_{s,t}})$ is the change of the natural logarithm of light, and ξ_t is a year fixed effect. γ is the coefficient (growth elasticity) that maps the growth in nighttime light intensity into a proxy for economic activity measurement, an indicator that tells whether nighttime light intensity is a good measure for economic activities in Nigeria or not. $u_{s,t}$ is the error terms or disturbances for each state s at time t .

b. Levels with two-way fixed effects linear regression model, as specified by Henderson et al. (2012).

$$\ln(GSDP_{s,t}) = \delta + \xi_t + \varrho_s + \gamma \ln(NTL_{s,t}) + u_{s,t}, \quad (17)$$

where ϱ_s is the state fixed effect and δ is a constant term.

3.5. Disaggregated States GDP Convergence Test

3.5.1. Unconditional Cross-Section β -Convergence Test

In formal terms, β -Convergence refers to a situation where economies or regions with lower initial values of a given variable, such as GDP per capita, productivity, or income, tend to grow faster than those starting at higher levels. This implies a process of catch-up, where poorer units close the gap with richer ones over time. Empirically, the concept is typically assessed by estimating a regression in which the subsequent growth rate of the variable is

related to its starting value. A significantly negative coefficient on the initial level indicates that higher starting points are associated with slower growth, consistent with convergence.. In empirical terms, this is often tested by estimating a regression of the form:

$$g_{i,t} \rightarrow t + H \equiv \frac{1}{H} \ln \left(\frac{y_{i,t+H}}{y_{i,t}} \right) = \alpha + \beta \ln y_{i,t} + \varepsilon_{i,t}, \quad (18)$$

where, $i = 1, \dots, N$ indexes states; $t = 1, \dots, T$ indexes years. $y_{i,t}$ is the real states GDP per capital of states i at time t . H is the horizon (3-year non-overlapping intervals), this interval period helps to avoid the issue of serial correlation and business cycle effects. β –Convergence has the following hypothesis: $H_0(\text{no convergence}): \beta \geq 0$; $H_1(\text{convergence}): \beta < 0 \Rightarrow$ poorer states grow faster. The speed of convergence (continuous-time) is as follows:

$$\lambda \approx -\frac{1}{H} \ln(1 + \beta H), \quad (19)$$

where Half – life = $\frac{\ln 2}{\lambda}$. When $|\beta H|$ is small, $\lambda \approx -\beta$.

3.5.2. Sigma (σ) Convergence

Sigma convergence focuses on whether disparities in GDP levels among regions, states, or countries shrink over time, signaling a trend toward more equal economic conditions. To assess this, researchers often examine the dispersion of the relevant economic indicator across units over multiple years. Two common approaches are variance analysis and the coefficient of variation, but we focus only on variance analysis in this studies.

Variance analysis: This approach measures the spread of economic performance by calculating the variance of the logarithm of real GDP per capita of states, for each year. For a given time t , the variance is computed using the logged values of y , where y represents the real GDP per capita measure of interest across all units in the sample. A downward trend in this variance over time indicates σ -convergence. The formula for the variance of log of the real GDP per capita y at time t for each state is:

$$Var(\ln y_t) = \frac{1}{N} \sum_{i=1}^N (\ln y_{i,t} - \overline{\ln y_t})^2, \quad (20)$$

where: N is the number of states, $\ln y_{i,t}$ is the natural logarithm of the real GDP per capita of states i at time t , $\overline{\ln y_t}$ is the mean of the natural logarithms of the real GDP per capita of states at time t . If the variance $Var(\ln y_t)$ decreases over time, it indicates sigma convergence.

3.5.3. Panel Regression (States & Time Effects)

The regression is of the form:

$$\ln(y_{i,t}) = \beta \ln y_{i,t-1} + \mu_i + \tau_t + \varepsilon_{i,t}, \quad (21)$$

where μ_i are state fixed effects (unobserved heterogeneity) and τ_t are year effects. $\beta < 0 \Rightarrow$ convergence. Driscoll-Kraay standard errors approach was employed to correct for cross-sectional dependence, heteroskedasticity, and serial correlation. Although the dynamic fixed-effects estimator is subject to downward Nickell bias because the lagged dependent variable is

correlated with the transformed error term, the bias declines as the time dimension increases. With $T = 15$, the bias is expected to be smaller than in very short panels. Therefore, the fixed-effects estimates are compared with results from a consistent dynamic-panel estimator as a robustness check.

3.6. An Overview of Nighttime Light Data and GDP data

Nighttime lights serve as a common substitute for gauging economic activity in instances where official statistics are lacking. They are also increasingly utilized to analyze the impacts of disruptions or policy changes on a localized level. The underlying presumption is that nighttime lights can effectively capture fluctuations in GDP without being influenced by the specific attributes of the area being studied or the level of aggregation employed. The Earth Observation Group, housed within the NOAA National Centres for Environmental Information (NCEI), determines the intensity of nighttime lights from imagery. This data is sourced from two primary programs: the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS) and the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) series (Elvidge et al., 2021), which offer valuable insights into human activity and environmental phenomena globally (Gibson et al., 2020).

The NOAA/NGDC released the DMSP/OLS nighttime lights time series data covering the period from 1992 to 2013. The DMSP/OLS data is categorized into three main types: stable light data, cloud-free coverages, and unfiltered data. For the purposes of this study, the DMSP/OLS stable light data from 1992 to 2013 were collected. This dataset comprises a cloud free composite constructed from all smooth resolution data archives of DMSP/OLS. It specifically includes lighting from cities, towns and other locations with persistent illumination, while excluding ephemeral events such as fires, gas flares, volcanoes and background noise. The spatial resolution of this dataset is 30 arc seconds, and it can be accessed from the following link: <http://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html>.

In comparison to the DMSP/OLS data, the NPP/VIIRS data offers higher spatial resolution and a broader radiometric detection range. Furthermore, NPP/VIIRS data benefits from onboard calibration, enhancing data quality, a feature not available in DMSP/OLS data. The Suomi NPP/VIIRS DNB composite data used in this study is annual ranging from 2013 to 2023. The spatial resolution of the NPP/VIIRS data is 15 arc seconds and the composite nighttime light data can be accessed from the NOAA/NGDC website: http://ngdc.noaa.gov/eog/viirs/download_viirs_ntl.html.

Overall, we extracted data for Nigeria from the harmonized DMSP and VIIR NTL data from 1992-2021 at the global scale, available at (https://figshare.com/articles/dataset/Harmonization_of_DMSP_and_VIIRS_nighttime_light_

data_from_1992-2018_at_the_global_scale/9828827). These original data have undergone filtering to eliminate light detections associated with fires, volcanoes, auroras and background noise. Additionally, faint light reflected by snow-capped mountains and dry lake beds, has been subtracted (Wu & Wang, 2019).

The Gross Domestic Product (GDP) data in Naira at the national level is obtained from the Nigerian National Bureau of Statistics (NBS) for period covering 1992-2021 and the available annual GDP data at states level in Nigeria is obtained from the Nigerian NBS for 2013 to 2017 periods, in Naira.

4.0. Results and Discussion

The results of this study present a comprehensive assessment of the relationship between satellite-recorded Nighttime Lights (NTL) data and the economic performance of Nigerian states. By applying fixed-effects panel regressions and convergence analyses, the study demonstrates the methodological viability of using NTL as a proxy for estimating subnational GDP.

4.1. Results of the States GDP Disaggregation

The spatial distribution of estimated state-level GDP in 1992 in Figure 1 reveals a highly concentrated economic landscape, with the most intense activity located in the oil-producing coastal states of the Niger Delta, most notably Rivers, Bayelsa and Delta States, while much of the country, particularly the northern and north-central regions, exhibited relatively low economic output. This early pattern aligns with Nigeria's heavy dependence on oil exports during the early 1990s, where oil revenue was geographically concentrated and non-oil economic activity remained modest across much of the federation.

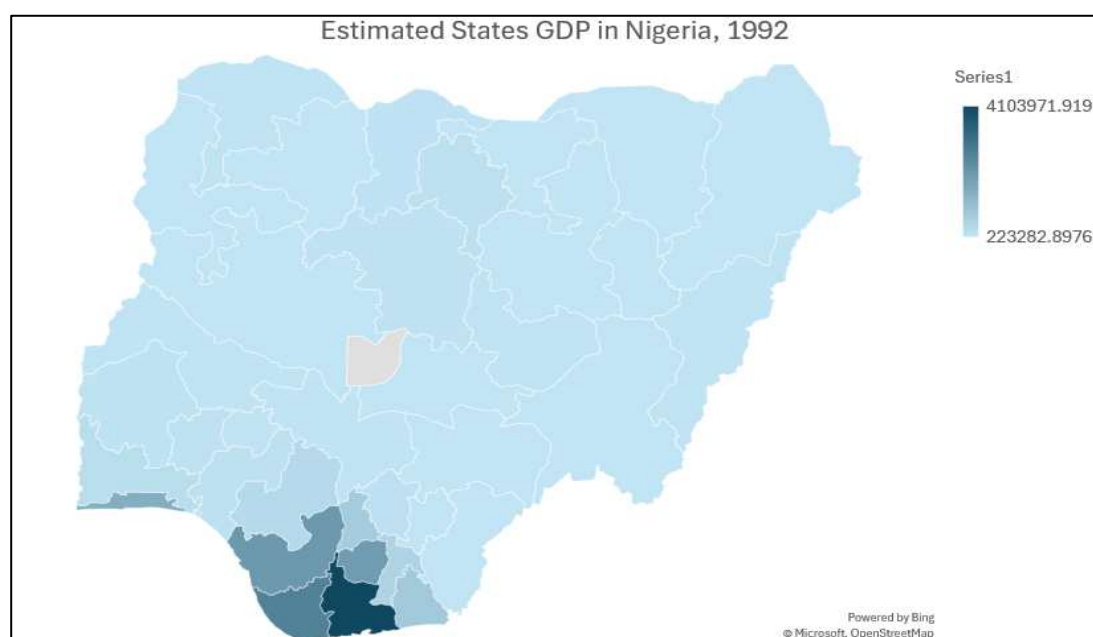


Figure 1: States GDP in Nigeria for 1992.

Source: Computed by the author.

Figure 2 shows that the distribution of GDP has undergone a notable transformation. While the Niger Delta remains a high-output region, new pockets of substantial GDP emerge in several inland states, particularly in the southeast (e.g., Anambra, Enugu) and northeast (e.g., Borno), as well as in key urban and industrial hubs such as Lagos, Kano and the Federal Capital Territory. This diversification in the spatial GDP pattern suggests two parallel dynamics: (i) the gradual diffusion of economic activity beyond oil-producing states into other regions, driven by industrialization, trade, and services; and (ii) a relative reduction in the dominance of oil states, reflecting both policy-led economic diversification efforts and changing patterns of investment and production.

The contrast between 1992 (Figure 1) and 2021 (Figure 2) also highlights a widening range in state-level GDP values. In 1992, the difference between the highest and lowest state GDP was largely driven by oil rents; by 2021, disparities reflect a broader combination of structural economic factors, including urbanization rates, infrastructure availability, human capital and security conditions. Notably, states such as Lagos and Kano maintain elevated GDPs due to their roles as major commercial and industrial centers, while certain inland states have significantly improved their relative positions, potentially indicative of targeted regional development policies or sectoral shifts (e.g., agriculture to manufacturing/services). Overall, these temporal snapshots provide compelling evidence of both persistence and change in Nigeria's economic geography. The enduring economic weight of oil-producing states underscores the continued influence of extractive industries, yet the emergence of multiple non-oil growth poles points to a slow but discernible structural transformation. For the full estimated States GDP data, refer to the appendix section of this paper.

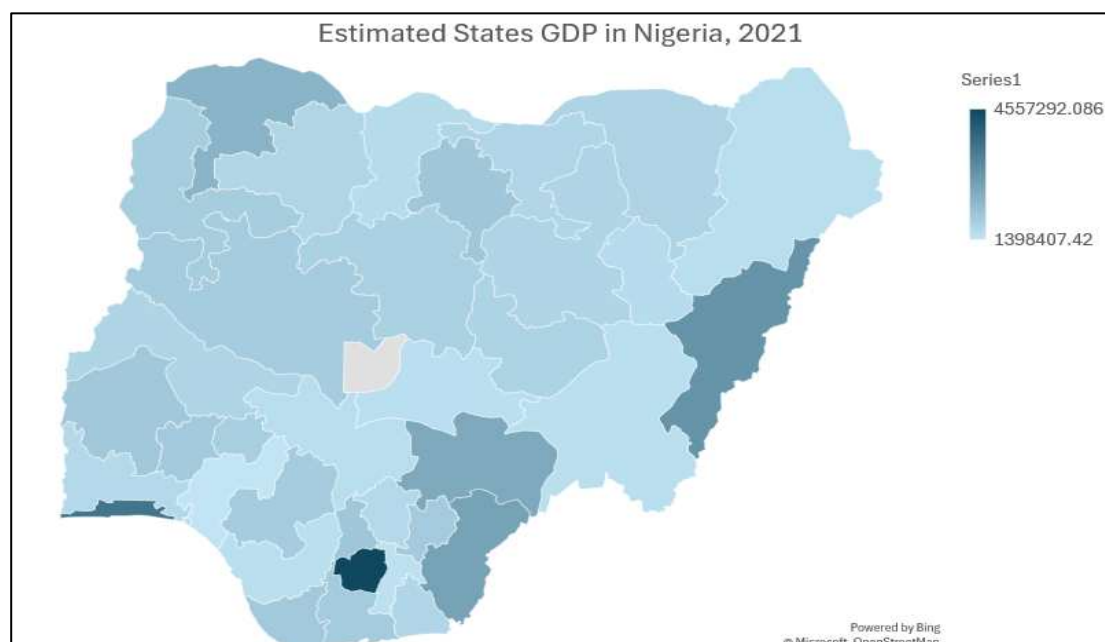


Figure 2: States GDP in Nigeria for 2021.

Source: Computed by the author.

Figure 3 compares Nigeria’s officially observed national GDP with the aggregated sum of state-level GDP estimates (GDP_allocated_sum) over the 1992–2021 period. The close alignment of the two series across all years suggests that the state-level allocation methodology preserves national totals with minimal aggregation error. Both series exhibit a steady upward trajectory from the early 2000s, reflecting Nigeria’s sustained economic expansion, particularly after 2004, with sharp increases coinciding with periods of oil price growth and broader macroeconomic gains. The minimal “diff” values indicate internal consistency between the national and state-level GDP figures, supporting the validity of the allocation framework used.

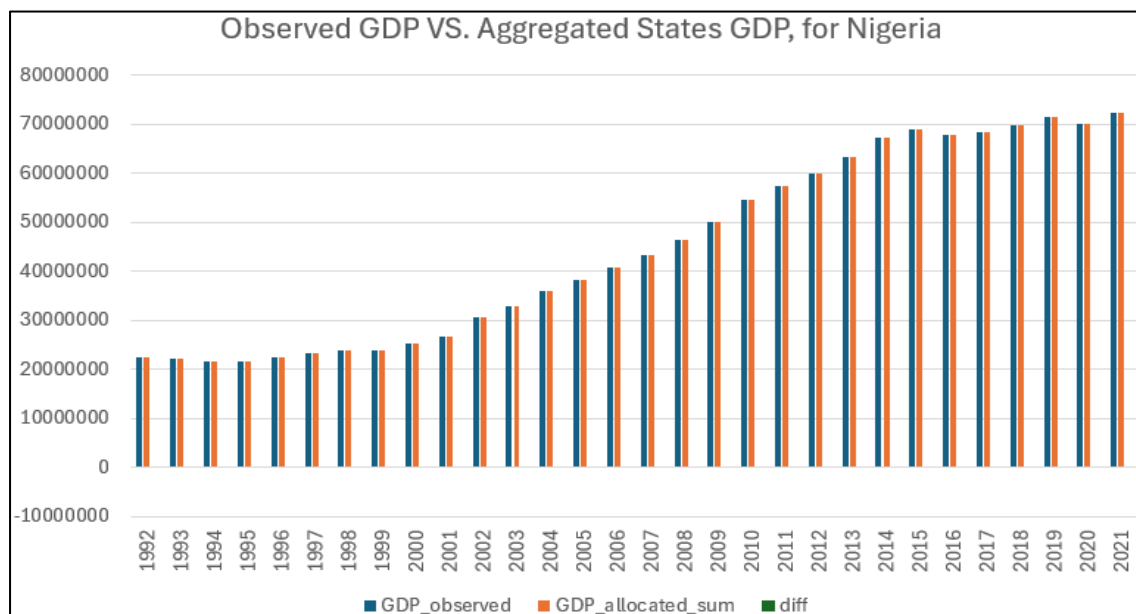


Figure 3: Observed GDP vs. aggregated States GDP (same as the GDP_allocated_sum) check.

Source: Computed by the author.

4.2. Comparing the Estimated State-Level GDP Data with Existing Official Data

Figures 4 and 5 compare the officially reported (“original”) and model-estimated GDP values for Nigerian states in 2013 and 2017. In both years, the estimates reproduce the general ranking of states by economic output but show systematic deviations for certain groups of states. The model tends to understate GDP for agriculturally dominant states such as Jigawa, Kaduna, Kogi, Niger, Ogun, and Gombe, where the economy is heavily reliant on crop production, livestock rearing, and fisheries. These sectors often involve dispersed rural activities and relatively low-intensity night-time illumination, leading to an underrepresentation of economic activity in NTL-based models despite substantial daytime productivity. A different set of factors contributes to the understatement for high-output states such as the Federal Capital Territory (FCT), Rivers, and Akwa Ibom. For the FCT, the

concentration of economic activity in government services, administrative functions and daytime-driven commerce is not well captured by night-time lights. In Rivers and Akwa Ibom, despite their strong oil and gas sectors, much of the economic value is generated in offshore or industrial facilities with limited night-time illumination, meaning the NTL signals do not fully reflect their economic scale. Conversely, the model tends to overstate GDP for states such as Ebonyi, Ekiti, and Ondo. In these cases, relatively dense settlement patterns and concentrated lighting in urban centers, combined with modest actual economic output, can inflate NTL-derived GDP estimates. This overestimation may also stem from localized non-productive lighting, such as street illumination projects or public facilities, that contributes to higher radiance levels without a proportional increase in GDP.

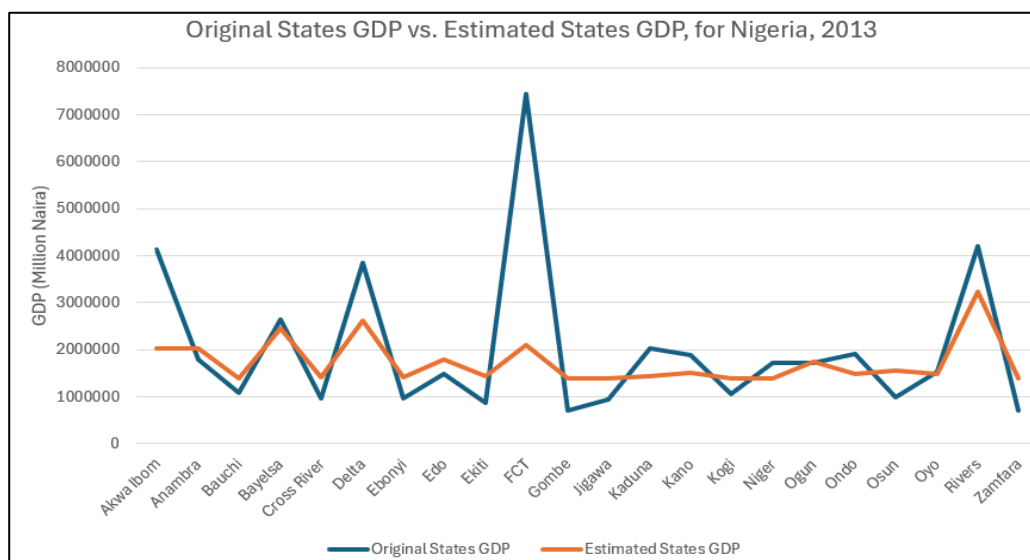


Figure 4: Original States-Level GDP vs. Estimated States-Level GDP, 2013.

Source: Computed by the author.

Between 2013 and 2017, the magnitude of absolute differences widens for several large economies, particularly the FCT and Rivers, reflecting both the rapid pace of economic expansion in these areas and structural shifts in their economic composition. Growth in administrative, service and extractive sectors during this period likely altered the spatial and temporal patterns of economic activity, creating greater divergence when compared with earlier years. The relatively consistent pattern of estimates across many other states suggests that underlying economic structures in those regions remained more stable, with fewer disruptive shocks or transformative investments. These variations point to the broader influence of sectoral change, infrastructure development and spatial concentration of industries in shaping the evolving GDP landscape across Nigeria's states.

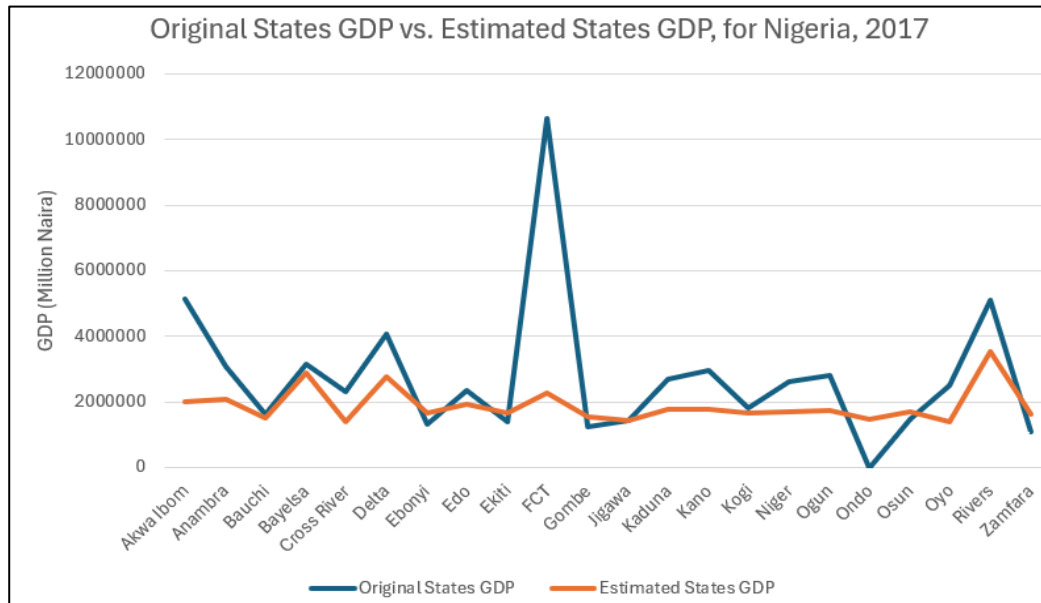


Figure 5: Original States-Level GDP vs. Estimated States-Level GDP, 2017.

Source: Computed by the author.

4.3. Results of the Relationship Between GSDP Growth Rates/Levels and States NTL Intensity Growth Rates/Levels.

4.3.1. Results for the Correlation Relationships between GSDP growth rates and NTL intensity Growth Rates, and Model Fitness Check.

The regression of changes in gross state domestic product ($\Delta \ln(\text{GSDP})$) on changes in night-time light intensity ($\Delta \ln(\text{NTL})$) yields a statistically significant growth elasticity of 0.096 ($p < 0.001$), indicating that a 1% increase in NTL intensity is associated, on average, with a 0.096% increase in GSDP, as captured in Figure 6 based equation (16). The standard error of 0.020 and the 95% confidence interval of 0.055 to 0.136 in Figure 6 and 7 suggest a reasonably precise estimate, with the lower bound still implying a positive and economically meaningful relationship. The model's R^2 of 0.458 shows that nearly half of the variation in GSDP growth rates across states is captured by changes in NTL, while the low RMSE of 0.07 suggests a good fit in relative terms.

$\Delta \ln(\text{GSDP})$ vs $\Delta \ln(\text{NTL})$	
Growth elasticity (γ)	0.096*** (0.020)
Num.Obs.	1073
R2	0.458
RMSE	0.07
Std.Errors	by: state
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001	

Figure 6: GSDP Growth Rates vs NTL Intensity Growth Rates Model Fitness Check.

Source: Computed by the author.

In the Nigerian context, this elasticity reflects the way night-time economic activity, as captured by artificial lighting, aligns with formal economic growth across states. Urbanized and industrial hubs such as Lagos, Rivers and the Federal Capital Territory often exhibit higher NTL growth that correlates strongly with rising GDP due to concentrated manufacturing, services and administrative functions.

```
> # Elasticity estimate and 95% CI
> confint(m1)["d_ln_ntl", , drop = FALSE]
                2.5 %    97.5 %
d_ln_ntl 0.05517143 0.136375
```

Figure 7: Elasticity Estimates and 95% Confidence Interval (CI).

Source: Computed by the author.

However, the moderate correlation of 0.29 between GSDP and NTL growth as shown in Figure 8 based on equation (16) underscores the structural complexity of Nigeria's economy, where substantial value is generated in sectors with low night-time light signatures, such as agriculture, artisanal mining and informal trade, particularly in rural states like Jigawa, Niger and Ekiti.

```
> # ---- Simple correlation of growth rates (uninformative about causality) ----
> with(est, cor(d_ln_gsd, d_ln_ntl, use = "complete.obs"))
[1] 0.2907183
```

Figure 8: Correlation of Growth Rates between GSDP and NTL Intensity.

Source: Computed by the author.

Additionally, oil-producing regions face NTL measurement distortions from gas flaring, which, even after data cleaning, can overstate radiance without proportionally reflecting economic

gains. These nuances highlight both the potential and the limitations of NTL-based models for tracking subnational economic performance in Nigeria's diverse and structurally heterogeneous economy.

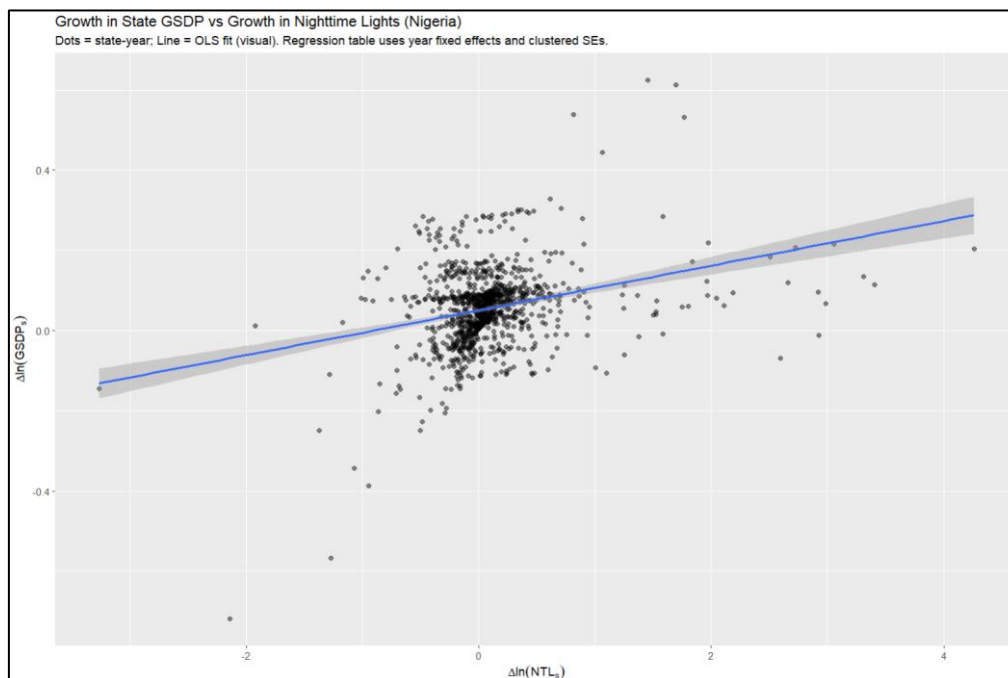


Figure 9: Raw Correlation plot (Unadjusted Relationship btw GDP growth and nighttime lights growth for Nigerian states.

Source: Computed by the author.

Figure 9 based equation (16) presents the unadjusted relationship between growth in state-level GDP and growth in night-time lights (NTL) for Nigerian states, showing a modest positive slope that indicates a general alignment between increases in illuminated activity and economic expansion. However, the raw correlation is relatively weak ($R^2 = 0.085$), reflecting the influence of year-specific macroeconomic shocks, national policy changes, and structural variations across states that can obscure the underlying association.

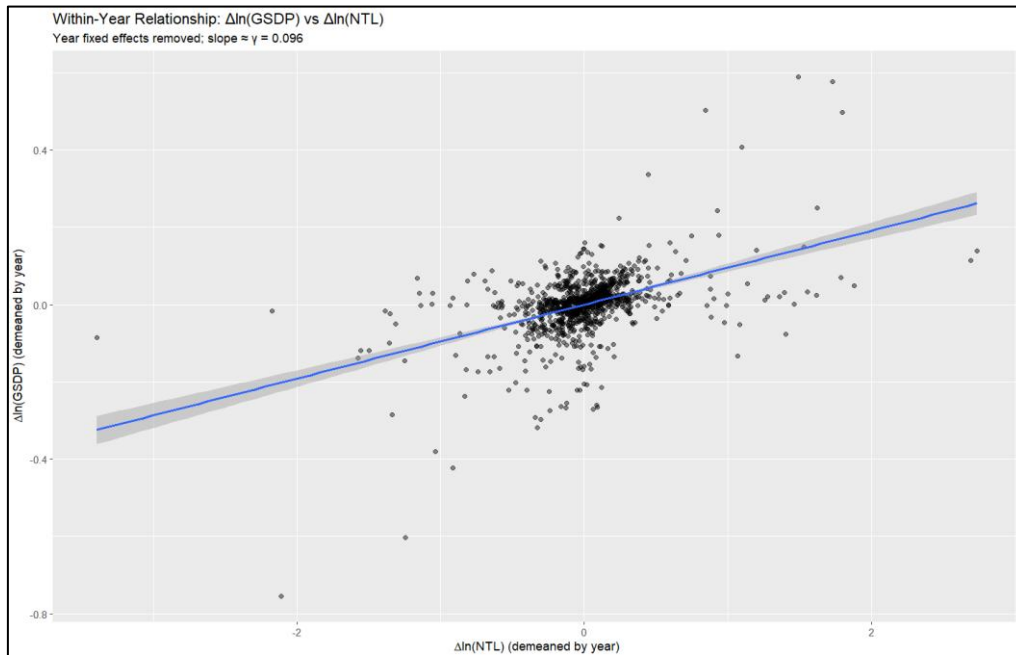


Figure 10: Year-adjusted (within-year) relationship between GDP growth and nighttime light growth for Nigerian states.

Source: Computed by the author.

Figure 10, based on equation (16), refines this picture by controlling for year fixed effects, thereby isolating the within-year relationship. The slope in this adjusted model remains positive, with a growth elasticity of approximately 0.096, and the fit improves substantially ($R^2 = 0.458$ overall; R^2 within-year = 0.221), highlighting that much of the noise in the raw correlation is attributable to inter-year macro-level fluctuations rather than the state-level link between NTL and GDP growth.

metric	value
<chr>	<dbl>
R^2 : OLS (no FE)	0.085
R^2 : OLS + year FE (overall fit)	0.458
R^2 : Within-year (demeaned, through origin)	0.221
Partial R^2 of $\Delta \ln(\text{NTL})$ year FE	0.221

Figure 11: Model Fitness Check.

Source: Computed by the author.

Figure 11, based on equation (16), further confirms the model's explanatory power by showing that, once year effects are accounted for, NTL growth alone explains around 22% of the variation in within-year GDP growth across states. In the Nigerian context, this finding suggests that while night-time lights provide a meaningful proxy for short-term economic changes, particularly in urbanized and industrialized regions, the relationship is far from complete. States with high-value economic activity in sectors less dependent on visible night-time illumination, such as agriculture-dominated northern states or offshore oil production

zones, remain less well-captured in this metric, reinforcing the need to complement NTL with other spatial-economic indicators when modelling subnational growth dynamics.

4.3.2. Levels Relationship between GSDP and NTL Intensity

The two-way fixed effects regression in Figure 12 based on equation (17), controlling for both state-specific and year-specific factors, reveals a statistically significant elasticity of 0.207 between NTL intensity and GSDP, with a standard error of 0.035. This implies that a 1% increase in night-time light intensity is associated with an average 0.21% increase in state-level GDP when accounting for time-invariant state characteristics and nationwide shocks.

ln(GSDP) on ln(NTL), FE(state,year)	
log(ntl)	0.207
	(0.035)
Num.Obs.	1110
R2	0.954
R2 Adj.	0.951
R2 Within	0.450
R2 Within Adj.	0.449
AIC	-707.5
BIC	-371.6
RMSE	0.17
Std.Errors	by: state
FE: state	X
FE: year	X

Figure 12: Levels with two-way FE (state & year) Relationship btw GSDP and NTL Intensity.

Source: Computed by the author.

The exceptionally high overall R^2 of 0.954 and adjusted R^2 of 0.951 indicate that the model explains the vast majority of variation in GSDP levels across states and years, while the within-state R^2 of 0.450 shows that nearly half of the year-to-year variation within individual states can be explained by changes in NTL intensity.

In the Nigerian context, this strong relationship underscores the usefulness of NTL as a proxy for spatial and temporal economic activity, particularly in urbanized and industrial centers such as Lagos, Rivers and the Federal Capital Territory, where night-time luminosity closely reflects underlying commercial, administrative and infrastructural activity. However, the elasticity value, being well below one, signals that growth in night-time lights only partially captures economic expansion, reflecting the structural reality that a significant share of Nigeria's GDP is generated in sectors with low illumination footprints, such as daytime agricultural production, informal trade and offshore oil extraction. Furthermore, the relatively high explanatory power is, in part, a result of controlling for fixed characteristics of states (e.g.,

geography, long-term infrastructure endowment) and common year shocks (e.g., oil price cycles, macroeconomic policy changes), which helps isolate the stable association between light emissions and economic performance. This suggests that while NTL-based models can be highly informative for monitoring subnational economic patterns, their interpretation must remain grounded in Nigeria's sectoral composition and regional heterogeneity.

4.4. Results of the Estimated States GDP Convergence Tests

The unconditional β -convergence regression in Figure 13 based on equation (18) yields a statistically significant negative coefficient for initial GDP per capita ($\beta = -0.02767$, $p < 0.001$), indicating that Nigerian states with lower initial income levels tend to grow faster than wealthier states, consistent with the hypothesis of absolute convergence. The magnitude of the coefficient translates, in Figure 14 based on equation (19), to an annual speed of convergence (λ) of approximately 2.89%, implying that disparities in per capita GDP between states diminish gradually over time. The corresponding half-life of about 23.99 years suggests that it would take nearly a quarter of a century for half of the initial income gap between poorer and richer states to close under current dynamics.

In the Nigerian economic context, this slow pace of convergence underscores the persistence of structural and institutional barriers to rapid equalization in regional economic performance. While poorer states may experience higher relative growth rates, the process is prolonged by factors such as disparities in infrastructure investment, educational attainment, security conditions, and sectoral economic bases.

```
> model_3year <- lm(
+   growth_rate ~ log_initial_gdp,
+   data = panel_3year
+ )
> summary(model_3year)
```

Call:
lm(formula = growth_rate ~ log_initial_gdp, data = panel_3year)

Residuals:

Min	1Q	Median	3Q	Max
-0.079682	-0.022571	0.006398	0.023872	0.093936

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	-0.007465	0.006952	-1.074	0.285
log_initial_gdp	-0.027667	0.005907	-4.684	6.38e-06 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.03338 on 146 degrees of freedom
Multiple R-squared: 0.1306, Adjusted R-squared: 0.1247
F-statistic: 21.94 on 1 and 146 DF, p-value: 6.378e-06

Figure 13: Unconditional Beta Convergence Estimates for States GDP per capita.

Source: Computed by the author.

Oil-producing and urbanized states, such as Rivers and Lagos, maintain a structural advantage due to resource rents, industrial agglomerations, and diversified service sectors, whereas many agrarian northern states remain constrained by limited capital inflows, lower productivity in primary sectors, and vulnerability to climatic and security shocks.

```
Beta estimate: -0.02766687
Annual convergence speed: 0.02888282
Annual convergence speed (%): 2.888282 %
Half-life: 23.99859 years
```

Figure 14: Speed of convergence per year and half-life estimates.

Source: Computed by the author.

These findings imply that without targeted policy interventions, particularly in human capital development, infrastructure, and economic diversification, the natural market-driven convergence process will remain too slow to achieve significant spatial income equality within a policy-relevant timeframe.

```
Call:
lm(formula = sigma2 ~ Year, data = sigma_df)

Residuals:
    Min       1Q   Median       3Q      Max
-0.028601 -0.020360  0.002343  0.018943  0.038084

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  7.74884    2.79904   2.768   0.0160 *
Year        -0.00375    0.00139  -2.697   0.0183 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.02327 on 13 degrees of freedom
(1 observation deleted due to missingness)
Multiple R-squared:  0.3588,    Adjusted R-squared:  0.3095
F-statistic: 7.275 on 1 and 13 DF,  p-value: 0.01829
```

Figure 15: Sigma convergence test for GDP per capita across States in Nigeria.

Source: Computed by the author.

The sigma convergence test in Figure 15 based on equation (20) reveals a statistically significant negative time trend in the variance of log GDP per capita across Nigerian states (coefficient = -0.00375, $p < 0.05$), suggesting that income disparities between states have, on average, narrowed over the study period. Figure 16, based on equation (20), corroborates this finding, showing a gradual downward trend in dispersion from the mid-2000s to around 2016, consistent with σ -convergence dynamics. However, the post-2016 period is marked by a partial reversal, with variance increasing modestly, likely reflecting the economic disruptions from

Nigeria's 2016 recession, oil price shocks, and regionally asymmetric impacts of insecurity and structural weaknesses in agriculture-dependent states.

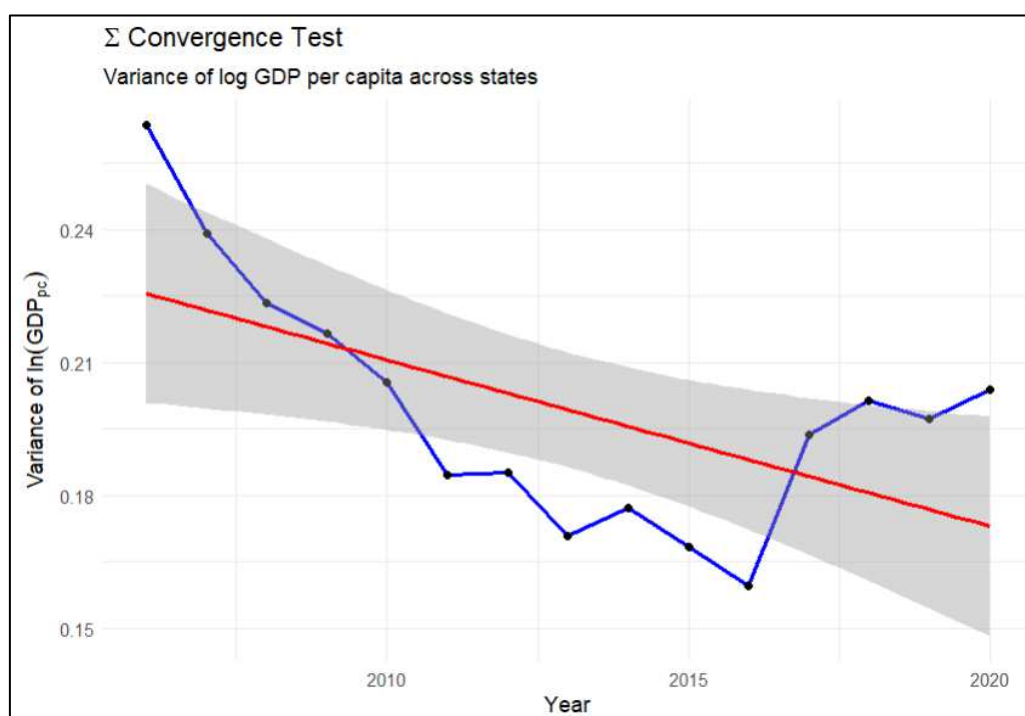


Figure 16: Variance of log GDP per capita across states in Nigeria.

Source: Computed by the author.

In the Nigerian context, the observed long-term decline in variance points to slow spatial equalization in per capita incomes, potentially aided by federal revenue-sharing mechanisms, expansion of internal trade, and infrastructure investments in lagging regions. Nonetheless, the recent uptick in inequality signals that convergence is not guaranteed and can be disrupted by macroeconomic shocks and region-specific vulnerabilities. The persistence of structural advantages in oil-producing and urbanized states, contrasted with climatic, security and infrastructural constraints in many northern and rural states, means that without sustained, regionally targeted policies, convergence gains risk being fragile and uneven across the federation.

$\Delta \ln(y)$ on $\ln(y_{t-1})$, FE(state,year)	
$\beta: \ln(y_{t-1})$	-0.248
	(0.027)
Num.Obs.	518
R2	0.440
RMSE	0.05

Figure 17: Conditional panel β -convergence regression with state and year fixed effects.

Source: Computed by the author.

The conditional panel β -convergence regression with state and year fixed effects in Figure 17 based on equation (21) yields a highly significant negative coefficient (-0.248, $p < 0.001$), confirming the presence of convergence in GDP per capita across Nigerian states once unobserved heterogeneity and time-specific shocks are accounted for. This coefficient implies a relatively rapid annual speed of convergence (λ) of 28.5%, corresponding to a half-life of approximately 2.43 years, meaning that half of the gap between poorer and richer states would close in less than three years under current dynamics when conditioning on structural factors and year effects.

```
> cat(sprintf("β estimate: %.4f\n", beta))
β estimate: -0.2482
> cat(sprintf("Speed of convergence λ: %.4f per year\n", lambda))
Speed of convergence λ: 0.2852 per year
> cat(sprintf("Half-life: %.2f years\n", half_life))
Half-life: 2.43 years
```

Figure 18: Speed of convergence and half-life for conditional panel regression of GDP per capita across states in Nigeria.

Source: Computed by the author.

Figure 18, based on equation (21), extends this insight to a multi-year horizon ($H = 3$), with a β estimate of -0.1965, implying an even faster effective convergence speed of 29.7% per year and a half-life of just 2.33 years. This suggests that when state-specific characteristics, such as institutional quality, sectoral composition, and long-term infrastructure endowments, are explicitly controlled for, regional incomes in Nigeria tend to converge at a pace far exceeding that implied by unconditional models.

```
> etable(m_beta_H, dict = c("ln_y_lag" = sprintf("β: ln(y_t), H=%d", H)), se.below = TRUE)
Dependent Var.:      m_beta_H
                   g_H
β: ln(y_t), H=3 -0.1965***
                (0.0170)
Fixed-Effects: -----
state          Yes
Year           Yes
-----
S.E.: Clustered by: state
Observations      444
R2                0.71860
Within R2         0.38465
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> cat(sprintf("\n[H=%d] β=%.4f, λ=%.4f/yr, Half-life=%.2f years\n", H, beta_H, lambda_H, half_H))
[H=3] β=-0.1965, λ=0.2969/yr, Half-life=2.33 years
```

Figure 19: Multi-years ($H = 3$) convergence test of GDP per capita across States in Nigeria.

Source: Computed by the author.

In the Nigerian economic context, these results in Figure 19 based on equation (21) indicate that substantial disparities in GDP per capita across states are, to a significant extent, explained by persistent structural factors rather than purely stochastic divergence. Once these structural differences are netted out, poorer states are catching up with richer ones at a relatively high rate, reflecting the potential of targeted investment, policy interventions, and intergovernmental fiscal transfers to accelerate convergence. However, the fact that such rapid convergence is conditional highlights the challenge: without addressing structural bottlenecks, such as inadequate infrastructure in the north, limited industrial diversification in the southeast, and volatility in oil-dependent states, unconditional convergence remains far slower, and spatial inequalities are likely to persist. This underscores the policy relevance of conditioning factors in shaping Nigeria's trajectory toward balanced regional development.

	m_beta_p.. d_ln_y	m_beta_dk d_ln_y
Dependent Var.:		
$\beta: \ln(y_{t-1})$	-0.2482*** (0.0272)	-0.2482** (0.0698)
Fixed-Effects:	-----	-----
state	Yes	Yes
Year	Yes	Yes
S.E.: Clustered	by: state	by: state & Year
Observations	518	518
R2	0.43965	0.43965

Signif. codes:	0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1	

Figure 20: Conditional panel beta convergence test vs. Driscoll-Kraay beta convergence test, for GDP per capita across States in Nigeria.

Source: Computed by the author.

Figure 20, based on equation (21), compares the results of the conditional panel β -convergence test with those obtained using the Driscoll-Kraay (DK) standard error correction for GDP per capita across Nigerian states. In both specifications, the estimated β coefficient is identical (-0.2482) and statistically significant, confirming robust evidence of conditional convergence irrespective of the standard error adjustment method. The consistency of the coefficient across models indicates that the speed of convergence, previously calculated at approximately 28.5% per year with a half-life of about 2.43 years, is not materially influenced by potential cross-sectional dependence or heteroskedasticity in the panel data. In the Nigerian economic context, this robustness strengthens the inference that poorer states are catching up with richer ones at a relatively rapid rate once structural differences and time-specific shocks are accounted for. The alignment between conventional and DK-corrected estimates suggests that spatial spillovers, common shocks (e.g., oil price volatility, national policy shifts), and correlated errors across states do not bias the convergence rate in a meaningful way. This

provides strong empirical support for the view that targeted, state-specific policy interventions, particularly those addressing infrastructure gaps, human capital disparities, and sectoral diversification, can significantly accelerate regional income equalization in Nigeria.

5.0. Conclusion, Findings, Recommendations and Limitations

This research has developed and applied a methodology for estimating state-level GDP in Nigeria using satellite-recorded Nighttime Lights (NTL) data. By integrating NTL intensity with econometric models, including fixed effects panel regressions, β - and σ -convergence tests, and elasticity estimation, the study demonstrates that NTL data provides a useful and good (though imperfect), proxy for capturing spatial and temporal variations in economic activity. The analysis reveals that NTL-based estimates broadly reproduce the ranking of states by GDP, correlate moderately to strongly with official statistics, and uncover evidence of both absolute and conditional convergence in per capita GDP across states. However, accuracy varies across regions, and structural limitations in NTL coverage, particularly in agriculture-dependent and offshore resource-based economies, require future methodological adjustments for improved reliability.

Key Findings

Based on the findings and conclusions of the study, the research questions are answered as follows:

NTL data can be effectively utilized for estimating Nigerian state-level GDP by calibrating luminosity data against known GDP figures using fixed effects regression to control for time-invariant state characteristics and common year shocks. The methodology should incorporate sectoral and geographic corrections, given the heterogeneous relationship between light intensity and actual production.

The study finds a statistically significant elasticity between GDP and NTL growth (~ 0.096 for growth rates; ~ 0.207 for levels) with R^2 values up to 0.95 when fixed effects are applied. This confirms a positive relationship but also shows that NTL captures only part of economic variation, requiring complementary indicators for sectors with low light output.

The estimated GDP values align closely with national aggregates and broadly reflect official state rankings. However, systematic underestimation occurs for agriculturally dominant states with low night activity (e.g., Jigawa, Niger, Kogi) and for high-value urban administrative centers (e.g., FCT) with daytime-driven economies. Overestimation occurs in some states where urban lighting is disproportionately high relative to economic output (e.g., Ebonyi, Ekiti, Ondo).

β -convergence tests indicate significant unconditional convergence at a slow pace (half-life ~ 25 years) and rapid conditional convergence (half-life ~ 2.4 years) when controlling for

structural factors. σ -convergence analysis shows a long-term decline in inter-state income variance, though recent years saw a partial reversal linked to macroeconomic shocks.

Is NTL a perfect proxy?: No. While highly informative, NTL is a good but not a perfect proxy for economic activity in Nigeria. Agricultural, informal and offshore sectors contribute substantial GDP without proportional night lighting. Gas flaring in oil states can also distort signals. NTL should be used in combination with other socioeconomic and geospatial indicators.

The methodology offers a cost-effective tool for near-real-time subnational GDP estimation, particularly valuable in contexts where official statistics are sparse or delayed. However, interpretation must consider sectoral biases and regional disparities in light use.

Recommendations

1. Integrate multi-source data: Combine NTL with sectoral indicators (e.g., agricultural production, port activity, energy consumption) to address underrepresentation of non-luminous economic activities.
2. Develop state-specific adjustment factors: Calibrate the model to account for known NTL distortions, such as gas flaring zones in oil-producing states or concentrated urban lighting in low-output economies.
3. Institutionalize NTL-based monitoring: Adopt NTL estimation within Nigeria's statistical agencies to complement official GDP figures, allowing more frequent subnational economic tracking.
4. Leverage for spatial policy targeting: Use the model outputs to identify underperforming regions, monitor economic shocks, and evaluate infrastructure or policy interventions in near-real-time.
5. Address structural barriers to convergence: Given the evidence of faster conditional convergence, policies should prioritize closing infrastructure and human capital gaps that slow unconditional convergence.

Limitations

Several limitations are acknowledged. Sectoral bias may arise because NTL tends to underestimate GDP in low-light sectors, such as agriculture and fisheries, while potentially overestimating economic activity in areas characterized by high levels of non-productive lighting or gas flaring. Data quality constraints also remain, as even after cleaning, NTL data may contain residual noise resulting from atmospheric interference, differences between sensors, or the concentration of artificial light in urban areas. Furthermore, temporal mismatches between the timing of economic activity and the capture of NTL observations may reduce the precision of the estimates. There are also limitations regarding causality, since

although the correlation between NTL and GDP may be strong, changes in nighttime light intensity do not fully explain changes in GDP, and economic activity may affect lighting patterns differently across states. Finally, the estimates may be sensitive to external shocks, such as recessions or insecurity, which can affect individual states disproportionately in ways that are not directly reflected in nighttime light intensity.

References

- Aboagye, S. and Turkson, E.F. (2013). An Empirical Investigation of Per Capita Income Convergence Hypothesis in Sub-Saharan Africa. *Department of Economics, University of Ghana*. <https://ugspace.ug.edu.gh/items/8cf249ca-87b0-43a7-a2cd-4542407331e7>
- Addison, D., & Stewart, M. (2015). Nighttime lights revisited: The use of nighttime lights data as a proxy for economic variables. *Remote Sensing*, 1-30. <https://ideas.repec.org/p/wbk/wbrwps/7496.html>
- Alemu, M., Jayamohan, M. K., & Mulugeta, W. (2025). Convergence in sectoral value-added and income per capita: Comparing fragile, resource, and emerging economies in Africa. *Research in Globalization*, 11. <https://www.sciencedirect.com/science/article/pii/S2590051X25000358>
- Aka, E. O. (2000). Regional disparities in Nigeria's development: Lessons and challenges for the 21st century. *University Press of America*. <https://www.semanticscholar.org/paper/Regional-Disparities-in-Nigeria%27s-Development%3A-and-Aka/de64570df3114ba579cba0147a59811c2bd0a3d0>
- Angelini, E., Henry, J., & Marcellino, M. (2006). Interpolation and backdating with a large information set. *Journal of Economic Dynamics and Control*, 30(12), 2693-2724.
- Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58(2), 277-297.
- Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics*, 68(1), 29-51.
- Baafi, J. A. (2018). Analysis of income convergence between Sub-Saharan Africa and high-income economies: Role of the components of trade. *Developing Country Studies*, 8(5), 25-55.

- Barro, R. J., & Sala-i-Martin, X. (1992). Convergence. *Journal of Political Economy*, 100(2), 223-251.
- Baumol, W. J. (1986). Productivity growth, convergence, and welfare: What the long-run data show. *The American Economic Review*, 76(5), 1072-1085.
- Ben-David, D. (1996). Trade and convergence among countries. *Journal of International Economics*, 40(3-4), 279-298.
- Bettendorf, T., & Bursian, D. (2017). Chow-Lin X N: How adding a panel dimension can improve accuracy? (*Discussion Paper No. 12*). *Deutsche Bundesbank*. <https://www.econstor.eu/bitstream/10419/158019/1/888101929.pdf>
- Bloem, A. M., Dippelsman, R. J., & Maehle, N. O. (2001). Quarterly national accounts manual: Concepts, data sources, and compilation. *International Monetary Fund*. <https://www.imf.org/external/pubs/ft/qna/2000/textbook/ch1.pdf>
- Bluhm, R., & McCord, G. C. (2022). What Can We Learn from Nighttime Lights for Small Geographies? Measurement Errors and Heterogeneous Elasticities. *Remote Sensing*, 14(5), 1-25.
- Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87(1), 115-143.
- Boot, J. C. G., Feibes, W., & Lisman, J. H. C. (1967). Further methods of derivation of quarterly figures from annual data. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 16(1), 65-75.
- Bundervoet, T., Maiyo, L., & Sanghi, A. (2015). Measuring national and subnational economic growth in Africa from outer space, with an application to Kenya and Rwanda. *Policy Research Working Paper*. <https://documents1.worldbank.org/curated/en/912151468188369841/pdf/WPS7461.pdf>
- Charpe, M. (2022). Night lights as a proxy for economic growth? An application to structural transformation. Employment Policy Department - ILO. https://www.ilo.org/sites/default/files/wcmsp5/groups/public/@ed_emp/documents/meetingdocument/wcms_836811.pdf
- Chen, B. (2007). An empirical comparison of methods for temporal disaggregation at the national accounts. *Bureau of Economic Analysis*. https://nces.ed.gov/FCSM/pdf/2007FCSM_Chen-V-A.pdf
- Cholette, P. A. (1984). Adjusting sub-annual series to yearly benchmarks. *Survey Methodology*, 10(1), 35-49.
- Cholette, P. A., & Dagum, E. B. (1994). Benchmarking time series with autocorrelated sampling errors. *International Statistical Review*, 62(3), 365-377.
- Chow, G. C., & Lin, A. L. (1971). Best linear unbiased interpolation, distribution, and extrapolation of time series by related series. *Review of Economics and Statistics*, 53(4), 372-375.

Coetzee, C. E., & Kleynhans, E. P. J. (2021). Estimating economic activity of South African provinces using satellite technology: An econometric panel data application. *Remote Sensing Applications: Society and Environment*, 23(21). https://www.researchgate.net/publication/352449768_Estimating_economic_activity_of_South_African_provinces_using_satellite_technology_An_Econometric_Panel_Data_Application

Dagum, E. B., & Cholette, P. A. (2006). Benchmarking, temporal distribution, and reconciliation methods for time series. *Springer*. <https://www.census.gov/library/working-papers/2008/adrm/dagum-01.html>

Dagum, E. B., Cholette, P. A., & Chen, A. G. (1998). A unified view of signal extraction, benchmarking, interpolation and extrapolation of time series. *International Statistical Review*, 66(3), 245-269. <https://ideas.repec.org/a/bla/istatr/v66y1998i3p245-269.html>

Denton, F. T. (1971). Adjustment of monthly or quarterly series to annual totals: An approach based on quadratic minimization. *Journal of the American Statistical Association*, 66(333), 99-102.

Di Fonzo, T. (1990). The estimation of M disaggregate time series when contemporaneous and temporal aggregates are known. *The Review of Economics and Statistics*, 72(1), 178-182.

Di Fonzo, T. (2003). Temporal disaggregation of economic time series: Towards a dynamic extension. *European Commission*. https://ec.europa.eu/eurostat/documents/3888793/5816173/KS_AN-03-035EN.PDF/21c4417c-dbec-45ec-b440-fe8bf95661b7

Djennas, M., & Ferouani, B. (2014). Growth and income convergence in Africa. *Journal of Economics and Development Studies*, 2(4), 63-76.

Dufrénot, G., Mignon, V., & Naccache, T. (2009). The slow convergence of per capita income between the developing countries: “Growth resistance” and sometimes “growth tragedy”. *CREDIT Research Paper No. 09/03, University of Nottingham*. <https://www.econstor.eu/obitstream/10419/65423/1/607314206.pdf>

Dufrénot, G., Mignon, V., & Naccache, T. (2012). Testing Catching-Up Between The Developing Countries: “Growth Resistance” And Sometimes “Growth Tragedy”. *Bulletin of Economic Research*, 64(4), 470-508.

Elvidge, C.D., Kimberly, B., Mikhail, Z., Feng, C.H., & Tilottama, G. (2021). VIIRS night-time lights. In *Remote sensing of night-time light*, pp. 6-25. *Routledge*. <https://www.routledge.com/Remote-Sensing-of-Night-time-Light/Elvidge-Li-zhou-Cao-Warner/p/book/9780367769888>

Eurostat. (2017). Handbook on quarterly national accounts. *Publications Office of the European Union*. <https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/ca-22-99-781>

Fernández, R. B. (1981). A methodological note on the estimation of time series. *The Review of Economics and Statistics*, 63(3), 471-476.

Galor, O. (1996). Convergence? Inferences from theoretical models. *Economic Journal*, 106(437), 1056-1069.

- Garang, A. P. M., & Erkekoğlu, H. (2021). Convergence triggers in Africa: Evidence from convergence clubs and panel models. *South African Journal of Economics*, 89(2), 218-245.
- Geweke, J., & Porter-Hudak, S. (1983). The estimation and application of long memory time series models. *Journal of Time Series Analysis*, 4(4), 221-238.
- Gibson, J., Olivia, S., & Boe-Gibson, G. (2020). Night lights in economics: Sources and uses. *LICOS Discussion Paper (No. 419)*. Katholieke Universiteit Leuven. <https://www.econstor.eu/bitstream/10419/230506/1/1688648216.pdf>
- Glodowska, A. (2015). Beta and sigma convergence within the European Union countries and regions. In *Proceedings of the 6th Global Conference on Managing in Recovering Markets, Cracow University of Economics*, 233-246.
- Guerrero, V. M., & Martínez, J. (1995). A recursive ARIMA-based procedure for disaggregating a time series variable using concurrent data test. *Scientific Research*, 4(2), 359-376.
- Hamman, N., & Phiri, A. (2022). Using nighttime luminosity as a proxy for economic growth in Africa: Is it a bright idea? *Managing Global Transitions*, 20(2), 139-165.
- Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica*, 50(4), 1029-1054.
- Henderson, J., Vernon, A. S., & David, N. W. (2012). Measuring economic growth from outer space. *American Economic Review*, 102(2), 994-1028.
- Hu, Y., & Yao, S. (2022). Illuminating economic growth. *Journal of Econometrics*, 228(2), 359-378.
- Huffman, W., & Huffman, N. (2018). Convergence theory and conditional convergence in countries of Sub-Saharan Africa from 1990-2015. *International Association of Agricultural Economists*.
- Infante, E. (2017). Two-step reconciliation of time series: new formulation and validation. *Università degli Studi di Napoli Federico II*. http://www.fedoa.unina.it/11731/1/Infante_Enrico_28.pdf
- Islam, N. (1995). Growth empirics: A panel data approach. *Quarterly Journal of Economics*, 110(4), 1127-1170.
- Islam, M. R. (2009). Evaluation of different temporal disaggregation techniques and an application to Italian GDP. *BRAC University Journal*, 6(2), 21-32.
- Kumo, W. L. (2011). Growth and Macroeconomic Convergence in Southern Africa. *Working Paper Series 314, African Development Bank*.
- Li, X., & Zhou, Y. (2017). A stepwise calibration of global DMSP/OLS stable nighttime light data (1992-2013). *Remote Sensing*, 9(6), 637. <https://doi.org/10.3390/rs9060637>
- Liu, H., He, X., Bai, Y., Liu, X., Wu, Y., Zhao, Y., & Yang, H. (2021). Nightlight as a proxy of economic indicators: Fine-grained GDP inference around Chinese Mainland via attention-augmented CNN from daytime satellite imagery. *Remote Sensing*, 13(11), 1-15.

- Lisman, J. H. C., & Sandee, J. (1964). Derivation of quarterly figures from annual data. *Journal of the Royal Statistical Society: Series C (Applied Statistics)*, 13(2), 87-90.
- Litterman, R. B. (1983). A random walk, Markov model for the distribution of time series. *Journal of Business and Economic Statistics*, 1(2), 169-173.
- Lopez-Ruiz, H. G., Blazquez, J., & Hasanov, F. J. (2019). Estimating the Saudi Arabian regional GDP using satellite nighttime light images. *King Abdullah Petroleum Studies and Research Center*. <https://app.amanote.com/v4.5.23/research/note-taking?resourceId=uqR0AXQBKQvf0Bhi-VOE>
- Mankiw, N. G., Romer, D., & Weil, D. N. (1992). A contribution to the empirics of economic growth. *Quarterly Journal of Economics*, 107(2), 407-437.
- Marcellino, M. (2007). Pooling-based data interpolation and backdating. *Journal of Time Series Analysis*, 28(1), 53-71.
- Monteiro, J., Martins, B., & Pires, J. M. (2018). A hybrid approach for the spatial disaggregation of socio-economic indicators. *International Journal of Data Science and Analytics*, 5(2-3), 189-211.
- Mveyange, A. (2015). Night lights and regional income inequality in Africa. *World Bank*. <https://www.worldbank.org/content/dam/Worldbank/Feature%20Story/Africa/afr-anthony-mveyange.pdf>
- Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica*, 49(6), 1417-1426.
- Nigerian National Bureau of Statistics. (2019). States nominal gross domestic product. <https://www.nigerianstat.gov.ng/elibrary/read/1066>
- Pérez-Sindín, X. S., Wójcik, P., Chen, T.-H. K., & Prishchepov, A. V. (2025). Can nighttime lights serve as a proxy for economic inequality at the local administrative unit scale? Evidence from Spain. *PLoS One*. <https://doi.org/10.1371/journal.pone.0319890>
- Pipien, M., & Roszkowska, S. (2015). Quarterly estimates of regional GDP in Poland – Application of statistical inference of functions of parameters. *NBP Working Paper No. 219*. https://static.nbp.pl/publikacje/materialy-i-studia/219_en.pdf
- Quah, D. (1993). Empirical cross-section dynamics in economic growth. *European Economic Review*, 37(2-3), 426-434.
- Quah, D. T. (1996). Empirics for economic growth and convergence. *European Economic Review*, 40(6), 1353-1375.
- Rossi, N. (1982). A note on the estimation of disaggregate time series when the aggregate is known. *The Review of Economics and Statistics*, 64(4), 695-696.
- Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. *Econometrica*, 26(3), 393-415.
- Silva, S. J. M. C., & Cardoso, F. N. (2001). The Chow-Lin method using dynamic models. *Economic Modelling*, 18(2), 269-280.

- Solow, R. M. (1956). A contribution to the theory of economic growth. *Quarterly Journal of Economics*, 70(1), 65-94.
- Stram, D. O., & Wei, W. W. S. (1986). A methodological note on the disaggregation of time series totals. *Journal of Time Series Analysis*, 7(4), 293-302.
- Suleiman, H. (2024). Illuminating the Nile: Estimating subnational GDP in Egypt using nighttime lights and machine learning. *GeoJournal*, 89(117), 2-19.
- Sutton, P. C., Elvidge, C. D., & Ghosh, T. (2007). Estimation of gross domestic product at sub-national scales using nighttime satellite imagery. *International Journal of Ecological Economics & Statistics*, 8(S07), 5-21.
- Wahiba, N. F. (2015). Convergence and divergence among countries. *Asian Economic and Financial Review*, 5(3), 510-520.
- Wane, A. A. (2004). Growth and convergence in WAEMU countries. *IMF Working Papers*. <https://www.elibrary.imf.org/view/journals/001/2004/198/article-A001-en.xml>
- Wang, T., & Sun, F. (2022). Global gridded GDP data set consistent with the shared socioeconomic pathways. *Scientific Data*, 9(221), 1-10.
- Wei, W. W. S., & Stram, D. O. (1990). Disaggregation of time series models. *Journal of the Royal Statistical Society: Series B (Methodological)*, 52(3), 453-467.
- Wu, K., & Wang, X. (2019). Aligning pixel values of DMSP and VIIRS nighttime light images to evaluate urban dynamics. *Remote Sensing*, 11(2), 1-18. <https://doi.org/10.3390/rs11121463>
- Yao, J. (2015). Nighttime lights data. <https://sites.google.com/site/jiaxiongyao16/nighttime-lights-data>
- Young, A. T., Higgins, M. J., & Levy, D. (2008). Sigma Convergence versus Beta Convergence: Evidence from U.S. County-Level Data. *Journal of Money, Credit and Banking*, 40(5), 1083-1093.

Appendix

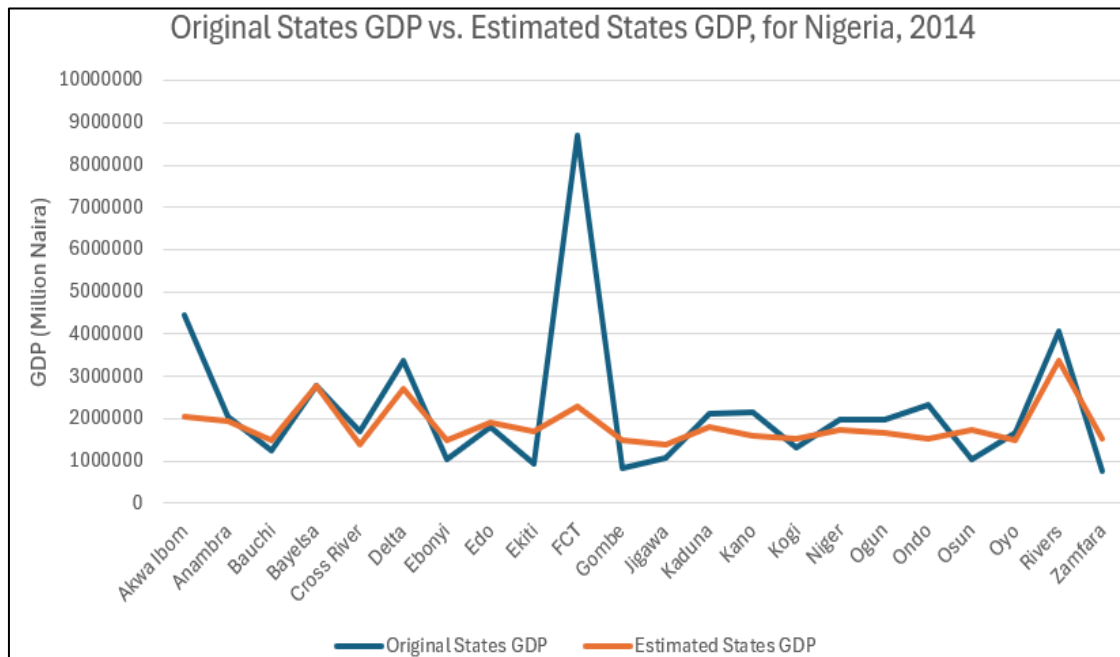


Figure 21: Original States-Level GDP vs. Estimated States-Level GDP, 2014.

Source: Computer by the author.

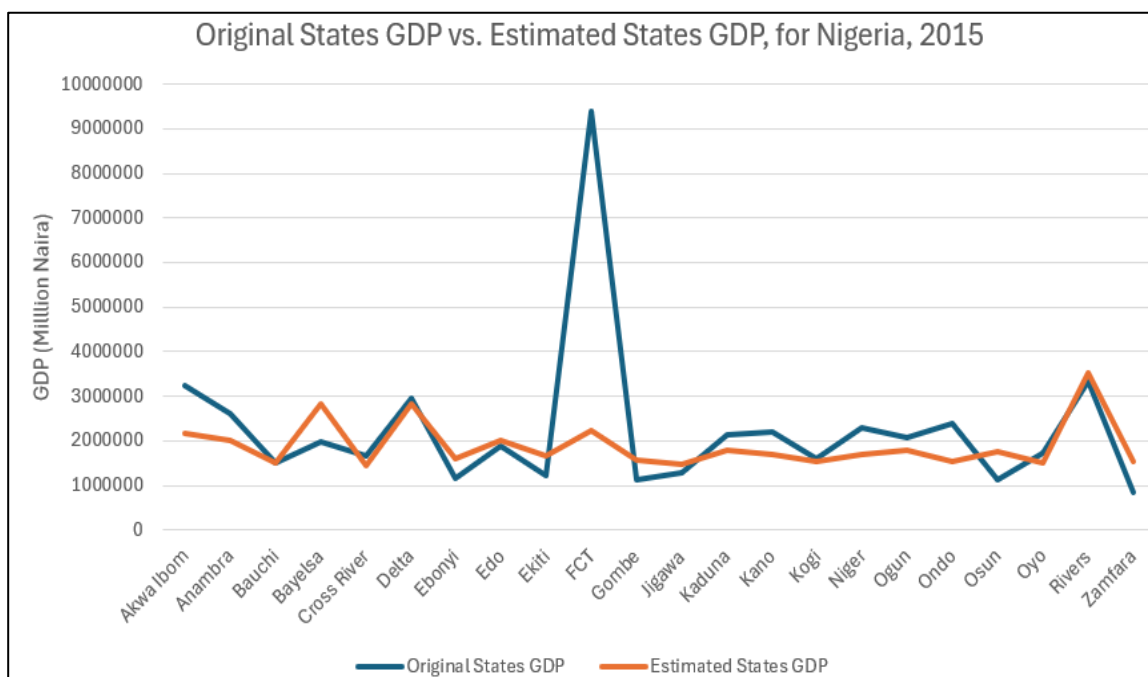


Figure 22: Original States-Level GDP vs. Estimated States-Level GDP, 2015.

Source: Computer by the author.

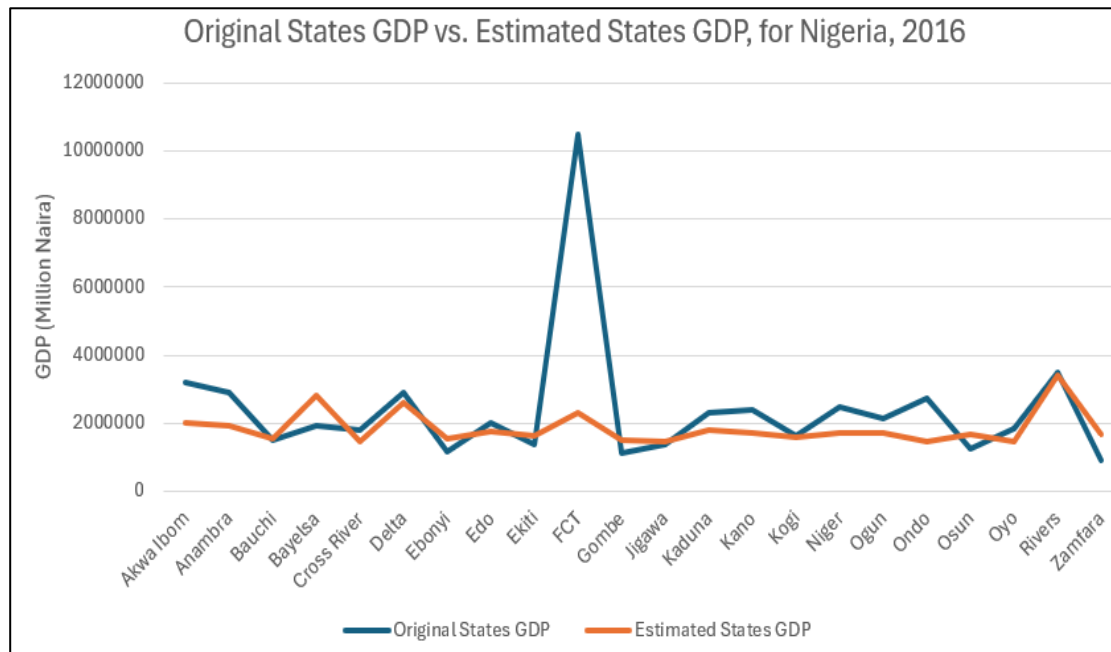


Figure 23: Original States-Level GDP vs. Estimated States-Level GDP, 2016.

Source: Computer by the author.

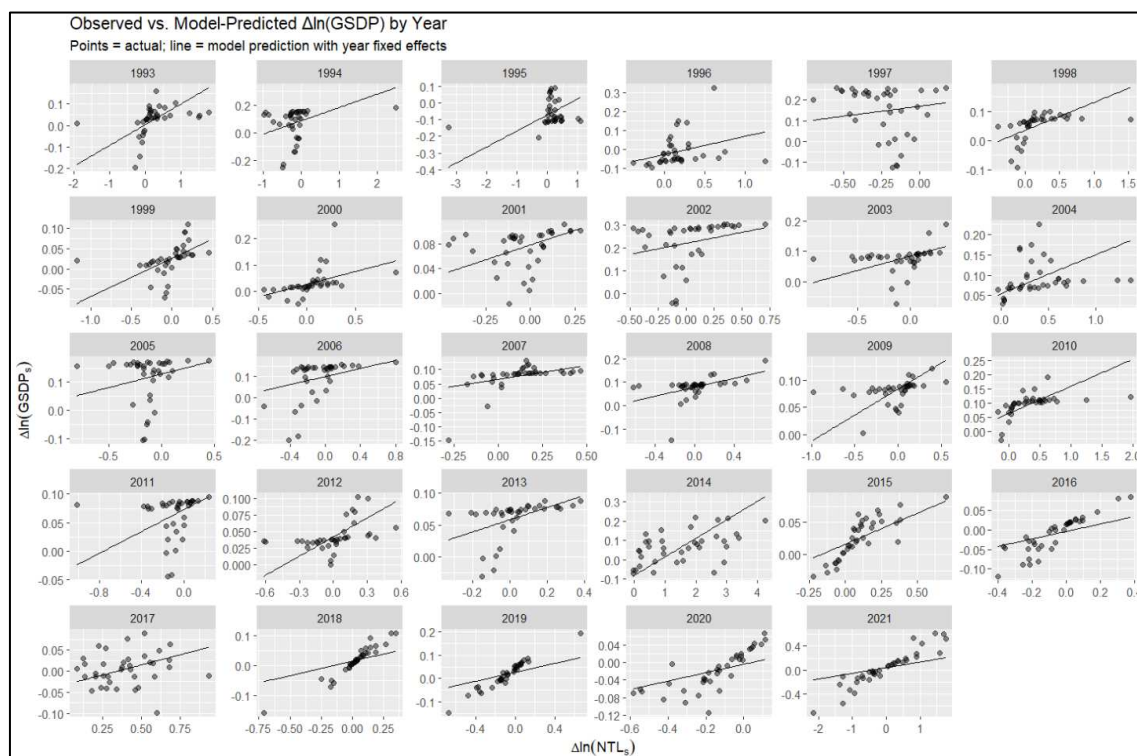


Figure 24: Observed vs. Model-Predicted GSDP Growth Rates by Year.

Source: Computer by the author.

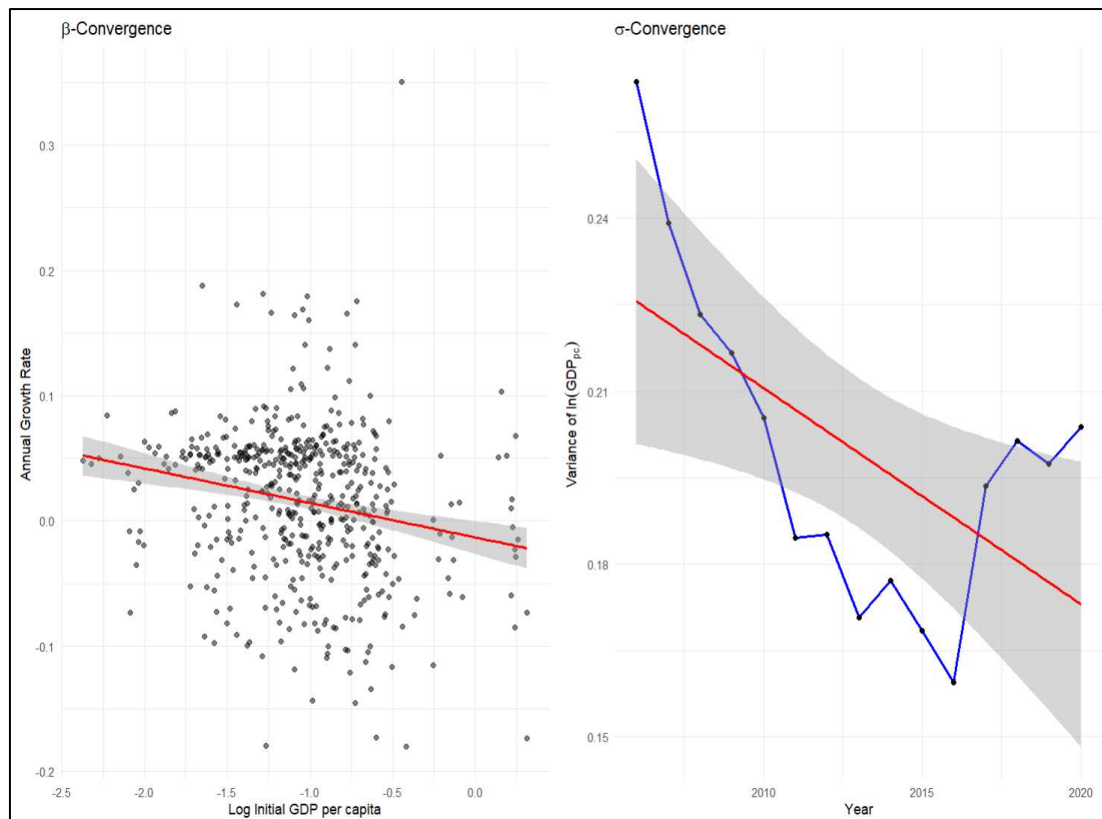


Figure 25: Beta and Sigma convergence test for GDP per capita across States in Nigeria.

Source: Computer by the author.

Note: RQ stand for research questions, the findings above answer all the asked research questions.

Year	Abia	Adamawa	Akwa Ibom	Anambra	Bauchi	Bayelsa	Benue	Borno	Cross Rive Delta	Ebonyi	Edo	Ekiti	
1992	649254.8	236705.6	901848.6	806302.7	229031.3	2680306	226037.5	233979.9	233350.1	2089630	223282.9	488807.1	238073.5
1993	709739.2	240257.9	743539.1	772272.8	235529.3	2319446	239005.3	242611.7	243610.2	2039421	240044.9	527774.5	264175.5
1994	564977.7	280700.8	579372.8	745134.3	274910.8	2231422	272425.2	280505.3	279721.2	1850645	273329.3	556758.7	285253.9
1995	619296.4	253106.8	471747.7	774283.3	246372.3	2397023	248449.8	253494.9	249762	1899449	245920.5	532654	263891.8
1996	632703.7	240829.3	654471.4	757101.4	233344.8	2788290	235765.8	238877	241769.9	2174964	234454	614582	249390.5
1997	639389	304778.5	745655.4	783774.5	297721.7	2490926	305283.6	301437.3	302749.3	1922344	300089.2	610676.4	312137.3
1998	595581.8	324644.7	782477.1	823357.4	320994.4	2274049	320755.4	324236.9	322562.5	1854982	328230.3	595651.1	328189.5
1999	651905.8	329989.6	820740.3	856309	327343.6	2178706	331937.2	330509.6	331847.9	1727057	331029.1	665747.4	335353.7
2000	731236.3	335297.5	784099.1	874168.4	333471.6	2810204	334233.5	335549.1	342994.4	1945685	355212.8	694883	338837.9
2001	719209.2	367728.2	866432.6	888336.6	367554.9	2873792	370002.4	367700.7	374664.8	2096696	380360.6	724763.3	370794
2002	775778.8	490124.5	971129.5	1071394	488137.2	2784025	494888.6	489392.9	497373	2012532	498973	815310.5	499103.8
2003	938663.2	536518.1	1063209	1140564	535112.1	2993949	532947	536359.9	539516.1	1871513	547871.6	870331.5	541091.2
2004	1176902	575916.7	1138429	1191636	572259.3	3108400	582198.4	577605.5	581832.1	2202082	600531.3	939983.1	581537.8
2005	1221974	681119.8	1309426	1341112	680686.3	2800323	684606.8	683917	695123.9	2111133	702584.4	958729.5	684696.6
2006	1253482	789238.7	1263227	1253669	788081.2	2336539	790348.1	788509.8	798151.6	1730623	803814.3	921248.7	809651.1
2007	1391309	857374.6	1417279	1410920	858236.8	2021789	862753.5	860058.5	869742.2	1818148	877215	967513	874666.7
2008	1400559	937804.9	1449732	1611834	936395.3	2190275	941637.9	938613.5	958071.9	2072401	954137.1	1173932	973981.5
2009	1508986	1025489	1591462	1684615	1021186	2375280	1029203	1024479	1036728	2313504	1038342	1177688	1066860
2010	1614357	1133983	1732211	1821012	1131793	2617571	1150200	1133904	1158397	2286816	1163787	1426153	1170592
2011	1648719	1238050	1838768	1816154	1235109	2504972	1243417	1234167	1254377	2393393	1254089	1544724	1287329
2012	1785364	1282527	2037344	1880353	1279900	2519949	1299024	1277197	1314300	2583600	1325483	1706713	1322440
2013	1891059	1381315	2031369	2039540	1380767	2444213	1391773	1375253	1405053	2615031	1421135	1788776	1444481
2014	2078792	1581168	2063845	1931918	1475781	2790708	1568243	1358886	1384384	2725287	1480857	1912316	1715276
2015	2190597	1617507	2163368	2006519	1514980	2830180	1646706	1486740	1454330	2829871	1599906	1999553	1668567
2016	2002174	1661184	2005852	1926631	1545458	2831232	1645714	1618729	1464276	2610679	1554879	1776066	1619478
2017	2034899	1618586	1995322	2081156	1525343	2877047	1665816	1552127	1400083	2768871	1656522	1943726	1679112
2018	2043033	1675732	1858375	2123522	1527216	2927793	1642216	1327773	1340502	3032701	1577552	1931620	1729523
2019	2038490	1674034	1957483	2186628	1467465	3042894	1725270	1614590	1418023	3229329	1617826	2007196	1726710
2020	1891792	1615234	1785649	2338240	1381987	2852049	1657488	1576659	1476596	3133641	1636964	2023132	1695633
2021	1474347	3017099	1691798	1978932	1713253	1937216	2582965	1540330	2723452	1527862	1897436	1881737	1820163

Figure 26: The estimated States GDP data in Nigeria.

The estimated States GDP data in Nigeria (continued).

Enugu	FCT	Gombe	Imo	Jigawa	Kaduna	Kano	Katsina	Kebbi	Kogi	Kwara	Lagos	Nassarawa	Niger
313474.2	403285.2	228220	1990641	224840.8	264003.9	320163.1	262246.6	226402.4	246245.9	238914.3	1571333	224642.9	231504.6
332198.7	472457.7	239386.7	1928624	238831.5	289536.6	330827.5	279594.1	234827.9	250911.9	250913.1	1618381	235637.9	240418.9
349735	540587.3	278279.2	1684022	276999.9	324761.4	366985.5	296858.5	273139.2	284873.3	283009.9	1555244	273584.5	280268.6
356861	530781.3	249615.4	1811641	249093.7	289986.1	339620.3	273371.5	245466.8	260294.5	257132.7	1693187	243188	250229.9
325511.4	541963.4	246999.7	1936580	235231.2	292994.8	338884.7	251625.4	230276.9	244306.9	245797.7	1664092	232607.1	236949.7
375139.6	534500.7	302565.4	1811186	298490.6	334691.9	392820.1	322046.9	294889.5	307282.4	306717.6	1686324	296299.3	300417.6
403610.6	589273.9	330379.6	1796075	324233.2	368646.5	417452.2	355447.6	318232.2	330267.2	325623.9	1697560	319258.7	321849.3
433163.9	645130.3	333512.3	1889479	334726.6	385553.8	442014.6	361601.1	327260.6	333939.1	333583.8	1703172	332356.4	333226.3
453268.7	697299.3	344679.6	1833864	337063.2	389653.6	426894.9	354691.7	333290	344206.1	340680.1	1713791	339821.9	342146.1
464715.6	754647.6	380187.6	1933837	372964.1	435902.8	472362.3	389738.9	363999.3	374878.1	368540.1	1847898	372346.2	373943.3
628461.2	894983.1	501125.3	2049978	489619.5	533553	582840	502582.9	487869.1	504158.5	499365.9	2196678	494319.7	498731.4
651518.1	874160.5	543614.2	2153918	532381.4	578140.9	630451.4	546809.2	536555.3	541045.2	539842.5	2187675	536304.1	538569.4
758002.6	1040823	582863	2220207	572922.4	620027.7	697560.1	598645.8	571762.7	587121.8	588078.9	2584975	584198.6	584625.6
863184.3	1099008	692241.4	2109996	677095.5	718849	795063.5	706822.3	678535.1	694525.2	690793.5	2563445	683631.9	688463.9
933427	1219056	793808.5	2078125	785157.1	827193.8	876943	806823.8	786507.8	804982.8	799635.9	2779281	794221.1	794161.3
1037396	1355694	872202	2371934	857787.4	907874.3	950998.9	881315.4	856606.7	873304.1	873383.9	2885066	871710.5	863731.5
1125272	1441849	941072.3	2464352	943441.7	987740.2	1028884	963562.8	937698.1	955421	953460.2	3055577	952423.8	944210.1
1188437	1511980	1036514	2564562	1019363	1065040	1117756	1034846	1020788	1033196	1040981	3314888	1042448	1026612
1383290	1747481	1146774	2490939	1140444	1196207	1256941	1164157	1131863	1152660	1156068	3429501	1159802	1143516
1445488	1808787	1252082	2492826	1246335	1295045	1368003	1264931	1234273	1256735	1258315	3500279	1265943	1243425
1538705	1965085	1294181	2571289	1294155	1347508	1402494	1307555	1281156	1300283	1300650	3550007	1319995	1289910
1650468	2091518	1398896	2574527	1399135	1446271	1506133	1405524	1379097	1402613	1410772	3697731	1414051	1391797
1921461	2297003	1488667	2393786	1388257	1798901	1596248	1524406	1546318	1541761	1539618	3501359	1500146	1725740
2034086	2246409	1567505	2456022	1465087	1782237	1700344	1589289	1559453	1545219	1489352	3728666	1475561	1703077
1937407	2287273	1495069	2246618	1470577	1809672	1723905	1613831	1553887	1573230	1536256	3549308	1544348	1735494
1912243	2257238	1535283	2369216	1451621	1789743	1758098	1620851	1584831	1651709	1563547	3570665	1478217	1711247
1805439	2392598	1602110	2349760	1472706	1814843	1780121	1645904	1693685	1723128	1742313	3750912	1646659	1815318
1925637	2350270	1489688	2546810	1507672	1886137	1768365	1661162	1673720	1619309	1506081	4014444	1558591	1743635
1997379	2421378	1388108	2658987	1436066	1805712	1690119	1633609	1538756	1707035	1536132	4033355	1570031	1675305
1632926	1716664	1580234	4557292	1706488	1787836	1976455	1585329	1870923	1546108	1714084	3639830	1515343	1873365

The estimated States GDP data (continued)

Ogun	Ondo	Osun	Oyo	Plateau	Rivers	Sokoto	Taraba	Yobe	Zamfara
397241.6	317329.5	291980	283350.9	244531.6	4103972	238726.2	227338.1	224101.9	225996.6
377243.1	338002.8	305753.3	291072.6	266203.4	3796304	247306.8	229992	233083	233136.6
387218.6	395521.9	323404.2	320821.2	296867	3308679	282166.4	276170.7	272185.7	270311.6
390581.1	379777.8	309261.6	298622.7	267317.6	3523511	259472	238987.5	243985.6	243049.8
383085	360800.7	318961.8	292521.4	256211	3714495	241066.9	224785.6	227401.1	229173.9
416559.1	426372.2	353509.7	347464.6	315459.8	3302660	308487.9	291583.6	293326.9	295365.9
452911	430953.5	374567.2	371777.4	342514.1	3485716	330712	313758.1	316399.9	316828.2
447960.3	411673.3	377997.5	370518.7	352978.8	3285646	343380.4	320329.2	324089.1	325823.7
462087.1	427135.1	395815.2	382850.8	358941.5	3332612	349850.6	327418.2	331516.4	334089.5
494865.7	448327.3	416255.2	408872.1	390265.5	3348182	384212	360237.7	364182.6	369225
650329.1	555086.5	562893	549948.3	507660	3205313	508451.7	481855.2	483783.9	487443
695992.5	606128	602509.8	588006.4	555735	3766489	560247.9	528523.9	530655.6	531876.4
795537.4	666443.9	690383.2	654023.9	593954.3	3919373	603913.2	564436.4	567760.6	580786.6
885745	758467.7	794821	755141	695505	3532585	712879.4	673295.3	674512.8	678756.3
1035626	872397.1	906031.3	861807.7	812054.6	3650426	807694.2	780440.7	781187.8	790107.9
1096183	954021.5	971820.1	938775.5	878220.4	3548074	889370.3	850559.7	851224.7	861618.8
1199136	1024573	1062084	1015950	955221.8	3065208	964466.3	931885.4	931298.4	935852.7
1333515	1156891	1159464	1111086	1036892	3232517	1046780	1018912	1017358	1017711
1454297	1240924	1277560	1226826	1158115	3437648	1168279	1131628	1126468	1150101
1525176	1337571	1390848	1323071	1255065	3295351	1258383	1226986	1228658	1244196
1602682	1387340	1431476	1374098	1306768	3296834	1310195	1277131	1274104	1292100
1735685	1480737	1562720	1489830	1400499	3227860	1411755	1375222	1371932	1384186
1676780	1527869	1720730	1475617	1721984	3386263	1321239	1686781	1280908	1523486
1795795	1532393	1745664	1494939	1708509	3526622	1343841	1664124	1307199	1553712
1709161	1468417	1684154	1466494	1756762	3412450	1376720	1697472	1335596	1684780
1756403	1482625	1691053	1409343	1675862	3517593	1361557	1713390	1210748	1619284
1789364	1486078	1743316	1514221	1708978	3532753	1423690	1774325	1216303	1637859
1817502	1575954	1773004	1462464	1700547	3749644	1497886	1758720	1309110	1785536
1877337	1561445	1798769	1486879	1594677	3346672	1400795	1744989	1303715	1742059
1635473	1398407	1920618	1965986	1749233	1898986	2384873	1527865	1733313	1689454