From Light to Growth: A Study of Night-Time Light as an Indicator of Economic Development*

Growth in Night-Time Light Intensity Correlates ____% With GDP Growth

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This study investigates the relationship between the growth of night-time light (NTL) intensity, as captured by satellite imagery, and GDP growth across countries over a multi-decade period. By analyzing data spanning from 1992 to 2001, we find a strong correlation of [X]% between NTL growth and GDP growth. Importantly, the strength of this correlation varies by the statistical capacity of countries. Countries with high statistical capacity, rated 'A' by the World Bank, exhibit a correlation as high as [X]%, while those with low statistical capacity, rated 'F', show a correlation as low as [Y]%. These findings highlight the potential of NTL data as a complementary tool for economic analysis, particularly in regions where conventional economic metrics are less reliable or unavailable.(Blank spaces will be filled when project is completed)

1 Introduction

2 Data

We collected data from multiple sources to analyze the relationship between night-time light intensity and GDP growth. The primary dataset is a harmonized global night-time light (NTL) dataset spanning from 1992 to 2018, developed by Li et al. (Li et al. 2020) The dataset combines observations from two satellite systems: DMSP/OLS (1992–2013) and VIIRS (2012–2018). To ensure consistency across years, they addressed differences in spatial resolution and saturation between the two systems by intercalibrating DMSP data and simulating DMSP-like VIIRS observations. The resulting dataset provides annual Digital Number (DN) values, representing night-time illumination intensity, as GeoTIFF files.

We also sourced GDP, manufacturing share of GDP, and population data from the World Bank's World Development Indicators (WDI) (The World Bank 2024b),measuring GDP in purchasing power parity (PPP) for comparability across countries. Additionally, we incorporated the Statistical Performance Indicator (SPI), which evaluates national statistical systems across five pillars: data use, data services, data products, data sources, and data infrastructure. (The World Bank 2024a) A thorough discussion on how we organised the data set is given in Section 2.2.

*Code and data are available at: https://github.com/shamayla38/EconomyLightCorrelation.

2.1 Measurement

Night-time light intensity, which reflects human activity, is indirectly measured by satellite sensors onboard the DMSP/OLS and VIIRS systems. These satellites capture light emissions from streetlights, industrial complexes, and residential areas, converting this physical phenomenon into Digital Number (DN) values. The brightness levels are then transformed into quantifiable data, which are stored in GeoTIFF format for further analysis. DMSP/OLS, operational since the 1970s, used low-light imaging to detect artificial lights but had limitations such as coarse resolution and sensor saturation (C. D. Elvidge et al. 1999). VIIRS, launched in 2012, provided better spatial resolution and could capture a wider range of light levels, with improved algorithms to filter out unwanted noise and natural light sources.(C. Elvidge et al. 2017). The harmonized version of these two datasets, combining data from DMSP/OLS and VIIRS, has been used by researchers for analysis.

GDP is measured as the total economic output of a country, adjusted for purchasing power parity (PPP) to standardize across different national economies. This transformation from an elaborate economic reality into a single numerical value is done through extensive national accounting systems, with data collected by governments through economic surveys, reports, and censuses.Population figures, reflecting demographic changes and the size of human capital, are also derived from national censuses and are measured in absolute numbers. Meanwhile, the manufacturing share of GDP is calculated by extracting relevant economic data, representing the portion of a country's GDP generated by the manufacturing sector. The World Bank sources all these data from national accounts.

2.2 Data Extraction and Cleaning

The data preparation began with extracting night-time light (NTL) intensity values from GeoTIFF files using Python's 'Rasterio' (Gillies et al. 2013--) package. This process involved reading annual TIFF files to obtain Digital Number (DN) values, representing light intensity, along with their corresponding latitude and longitude coordinates. This resulted in a spatial dataset detailing global NTL distribution for each year.

To associate each observation with a specific country, the extracted data were merged with a global shapefile of country boundaries through spatial join using (**geopandas?**). Each latitude-longitude pair was assigned to the country in which it was located, and observations without an assigned country—primarily from international waters—were removed. Subsequently, to create an aggregate annual measure of NTL intensity for each country, all observations within a country were summed to calculate the total light emitted annually.

The World Bank data, including GDP, manufacturing share of GDP, and population, were processed by standardizing country names to ensure consistency across datasets. For instance, discrepancies like 'Yemen' versus 'Yemen, Rep.' were resolved. The data were then transformed from a wide to a long format using pandas' 'melt' function, facilitating easier merging with the NTL data.

To assess how the correlation between night-time light (NTL) intensity and GDP varies among countries with differing levels of statistical capacity, we first to group countries together based on a measure of each country's statistical capacity.We used the World Bank's Statistical Performance Indicators (SPI). We calculated the average SPI score for each country across all the years SPI was available for and assigned grades based on these averages: scores of 80 and above received an 'A', scores between 60 and 79 a 'B', scores between 40 and 59 a 'C', scores between 20 and 39 a 'D', and scores below 20 an 'F'.A glimpse of the dataset is presented in Table 1.

Table 1: Sample of the dataset showing key variables used in the analysis

Country	Year	Night Lights (DN)	GDP (PPP)	Manufacturing Share	Population	Grade
Afghanistan	2002	37956	37931379899	18.822752	18.822752	C
Albania	1996	54902	17326597422	4.857952	4.857952	B
Algeria	1999	1634753	344181000000	34.479053	34.479053	C
Angola	1995	47138	72399259721	3.646281	3.646281	C
Antigua and Barbuda	1992	4162	1374028894	2.036987	2.036987	C
Argentina	1992	1427787	656388000000	21.859132	21.859132	B
Armenia	2012	160580	35673112560	9.424759	9.424759	A

Table 2: Summary Statistics of Data from year 1995 and 2020

	1995 (N=188)		2020 (N=189)	
	Mean	Std. Dev.	Mean	Std. Dev.
DN	1 412 963.5	5 631 142.1	2 971 421.4	9 552 808.9
GDP	369 356 559 423.2	1×10^{12}	776 024 587 843.4	3×10^{12}
Manufacturing	14.8	7.2	11.7	7.0
Population	14.8	7.2	11.7	7.0

DN refers to total average night-time light intensity emitted by a country in a year, GDP is measured in PPP, and Manufacturing refers to the manufacturing share of GDP.

2.3 Summary Statistics

It is more meaningful to examine the summary statistics year-wise to capture temporal variations in the data, as the variance across all years is substantial. Table 2 displays the summary statistics for selected years, showing significant growth in average night-time light intensity (DN), GDP (measured in PPP), and population from 1995 to 2020. An especially intriguing observation is that both night-time light intensity and GDP grew by almost exactly the same proportion—2.1 times—between 1995 and 2020 (DN increased by 2.102 times and GDP by 2.101 times).The summary statistics of the rest of the years are given in appendix.

2.4 Data Description

2.4.1 Night Time Lights Data

Nighttime light (NTL) distribution and intensity often vary significantly by population density, GDP, and levels of urbanization. When comparing countries with similar population sizes and land areas, the disparity in NTL intensity vividly reflects income inequality. A striking example is the contrast between North and South Korea, where South Korea's GDP per capita is over 50 times greater than that of North Korea, manifesting in the stark difference in nighttime illumination. In Figure 1, using NASA's Worldview NTL imagery, this difference of GDP is clearly visible, with South Korea brightly lit compared to its nearly dark northern neighbor. Similarly, Myanmar and Thailand, with comparable populations and land area, show a distinct NTL difference; Thailand's higher GDP and urbanization are evident in its dense and widespread lighting compared to Myanmar's relatively sparse illumination.

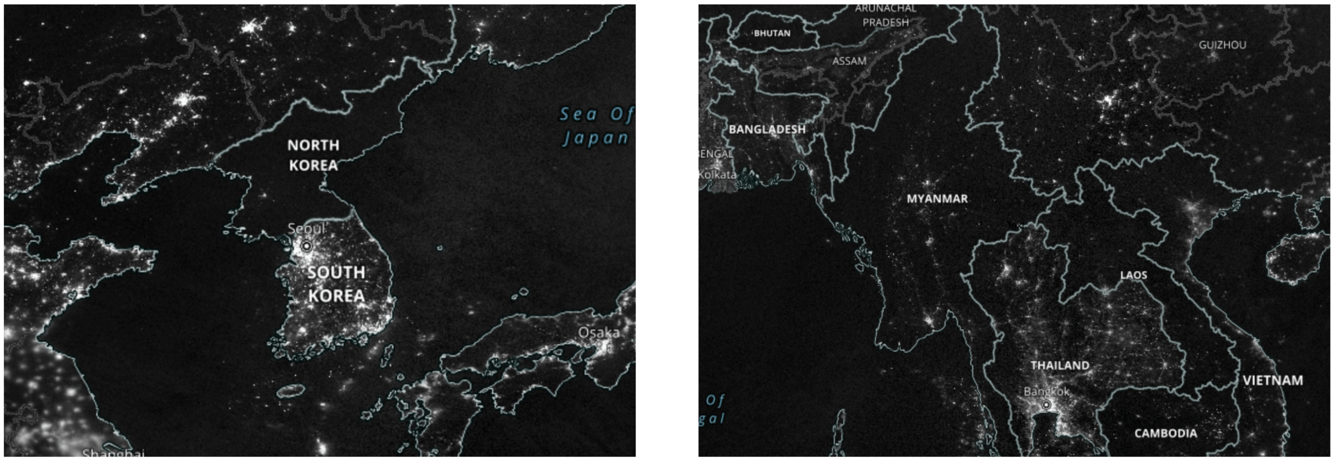

Figure 1: Night-time light intensity highlights stark contrasts in economic development: the profound disparity between North and South Korea, and the significant difference between Myanmar and Thailand.*(Source: NASA Worldview)*

Total night-time light (NTL) values for countries exhibit a highly skewed distribution due to the presence of a few highly luminous regions. In Figure 2, we observe that after applying a log transformation, this distribution becomes relatively normal, making it more suitable for comparative and statistical analysis

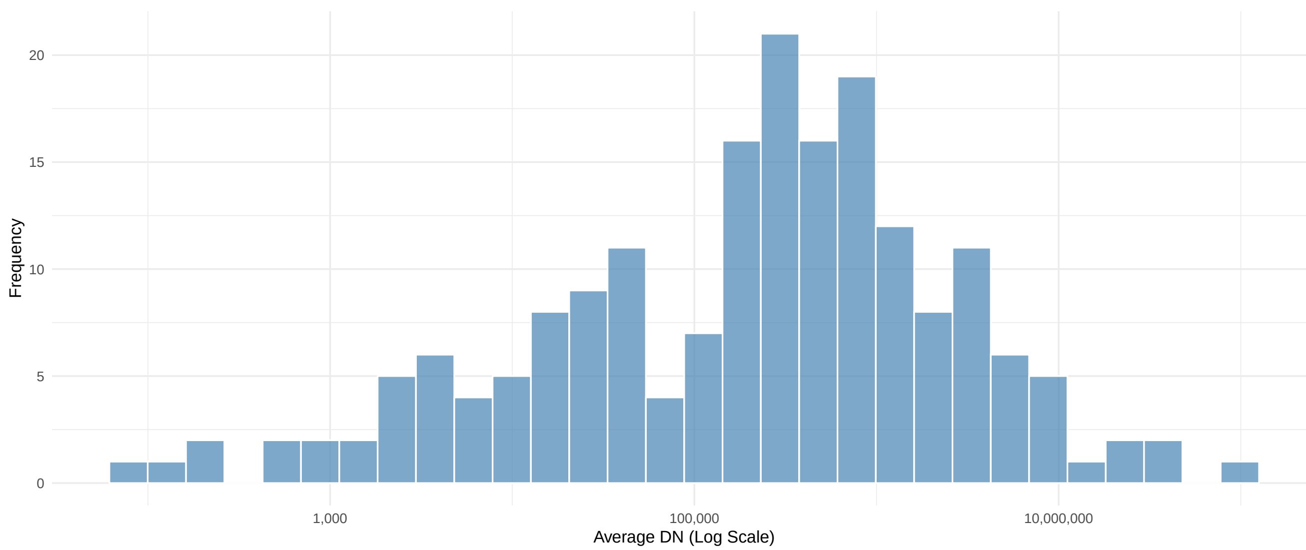

Figure 2: Distribution of log-transformed average nighttime luminosity (DN) by country over the past 30 years, showing variations in average brightness levels across nations.

2.4.2 GDP

To visualise GDP distribution across numerous countries, we categorized them into UN-defined SDG regions and examined the GDP distribution for 2012-2020. The Figure 3 shows that Europe and Northern America have the highest GDP levels, followed by Eastern and South-Eastern Asia and Latin America and the Caribbean, while Sub-Saharan Africa, Oceania, and Central and Southern Asia show significantly lower GDP levels. We would expect similar variations in night-time light intensity, with regions of higher GDP likely exhibiting brighter and more widespread night-time illumination. This connection underscores how night-time light can serve as a proxy for economic activity and development, reflecting the stark differences across regions.

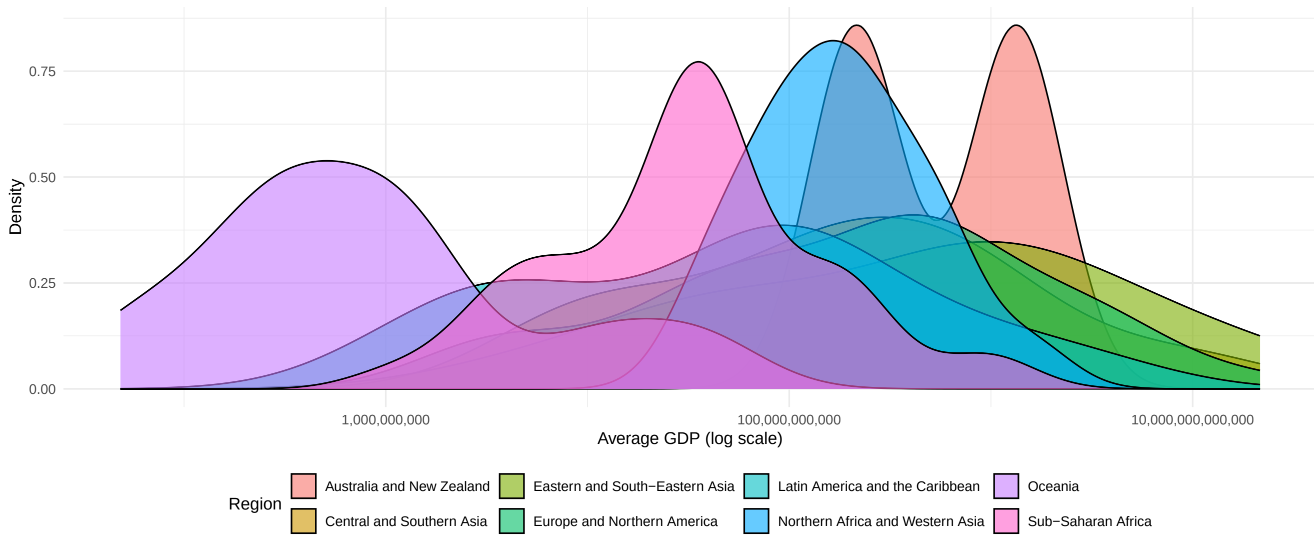

Figure 3: Density plot of average GDP (2012-2020) by region, illustrating Europe and Northern America with the highest GDP, followed by Eastern and South-Eastern Asia and Latin America and the Caribbean, while Sub-Saharan Africa, Oceania, and Central and Southern Asia exhibit significantly lower GDP levels.

2.4.3 Manufacturing Share of GDP of Country

Night-time light intensity is expected to vary with the share of manufacturing in a country's GDP, as higher manufacturing activity typically involves more factories, industrial areas, and infrastructure requiring artificial lighting. Figure 10 in appendix illustrates the manufacturing share of GDP for countries in 2020. Most countries have a manufacturing share below 20%, with a few exceptions such as Puerto Rico, Liechtenstein, and Ireland, which have some of the highest manufacturing contributions. Figure 11 in the appendix presents the manufacturing share of GDP at the beginning of our dataset's time frame in 1992, highlighting how many countries have gradually shifted towards a higher reliance on manufacturing over the years.

2.4.4 Population

Population trends provide essential context for understanding economic activity and night-time light (NTL) intensity patterns. In Figure 4, the total world population is shown to have grown steadily from approximately 4 billion in 1992 to over 7.5 billion by 2020. Figure 5 provides a regional breakdown of average population across intervals, categorized by UN-defined SDG regions. It reveals that regions like Central and Southern Asia and Eastern and South-Eastern Asia consistently have the highest average populations, while regions like Oceania and Sub-Saharan Africa have significantly lower averages. This demographic variation is critical for analyzing NTL because densely populated regions are likely to exhibit higher light intensity due to concentrated urbanization and industrial activity. Conversely, less populated or sparsely developed regions are expected to have lower NTL levels.

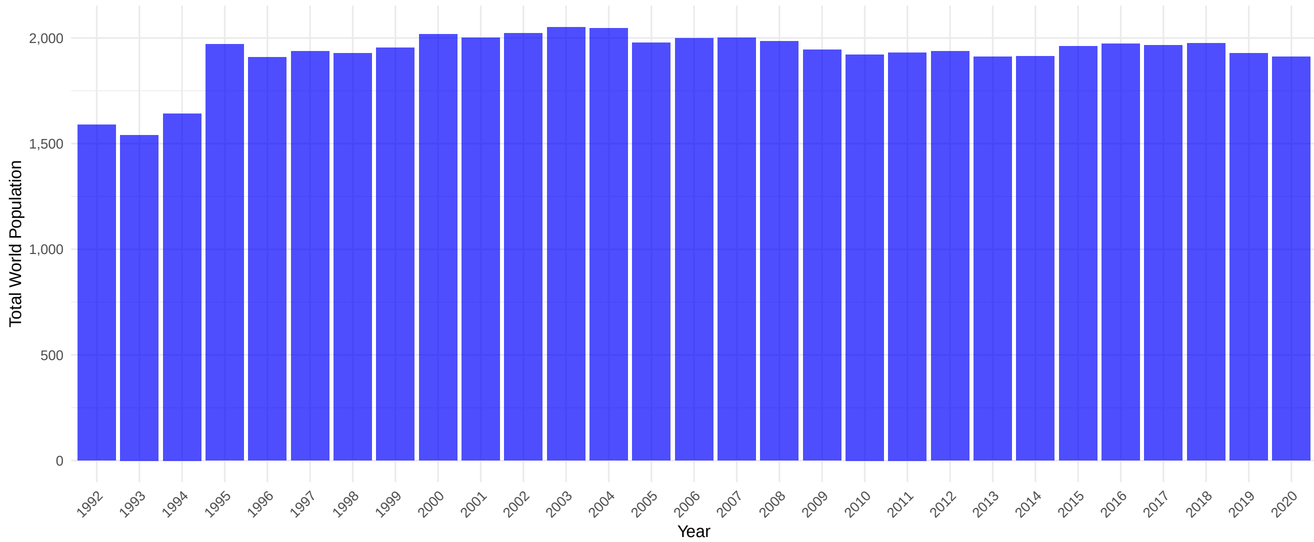

Figure 4: Steady growth of the global population from 1992 to 2020

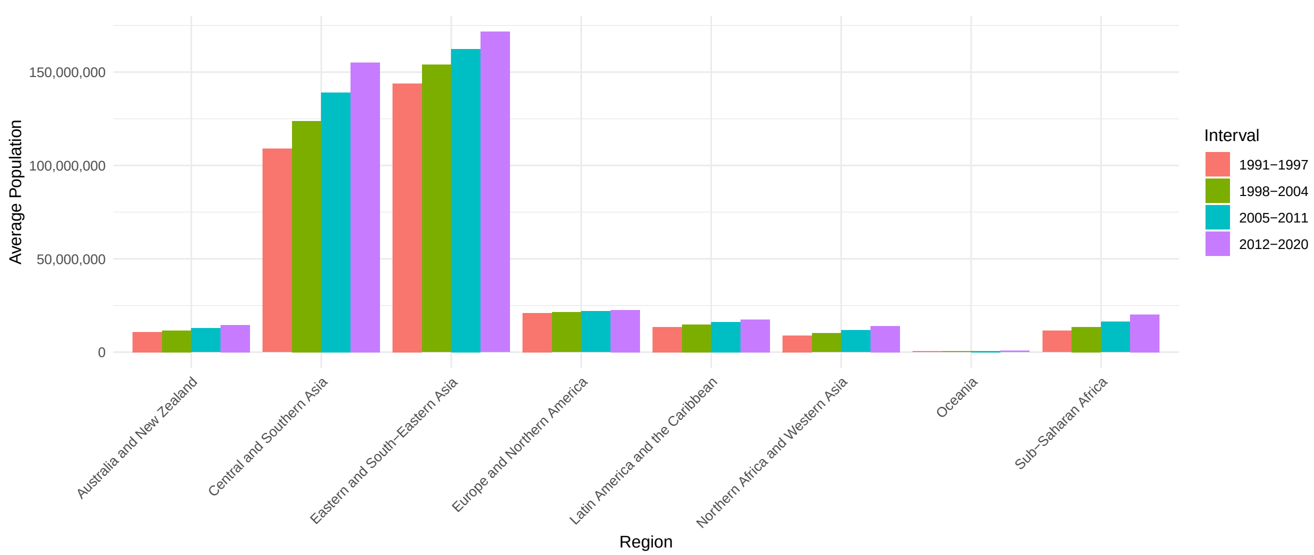

Figure 5: Average population (log scale) across regions for different time intervals (1991–1997, 1998–2004, 2005–2011, and 2012–2020) showing significant population growth in regions such as Central and Southern Asia, Eastern and South-Eastern Asia, and Sub-Saharan Africa over time, with variations across other regions

3 Night lights and GDP

Figure 6 plots the log of DN values against the log of GDP for all countries across 30 years, capturing the relationship between night-time light intensity and economic activity. The scatterplot shows a clear positive correlation, indicating that higher GDP values are generally associated with higher DN values.

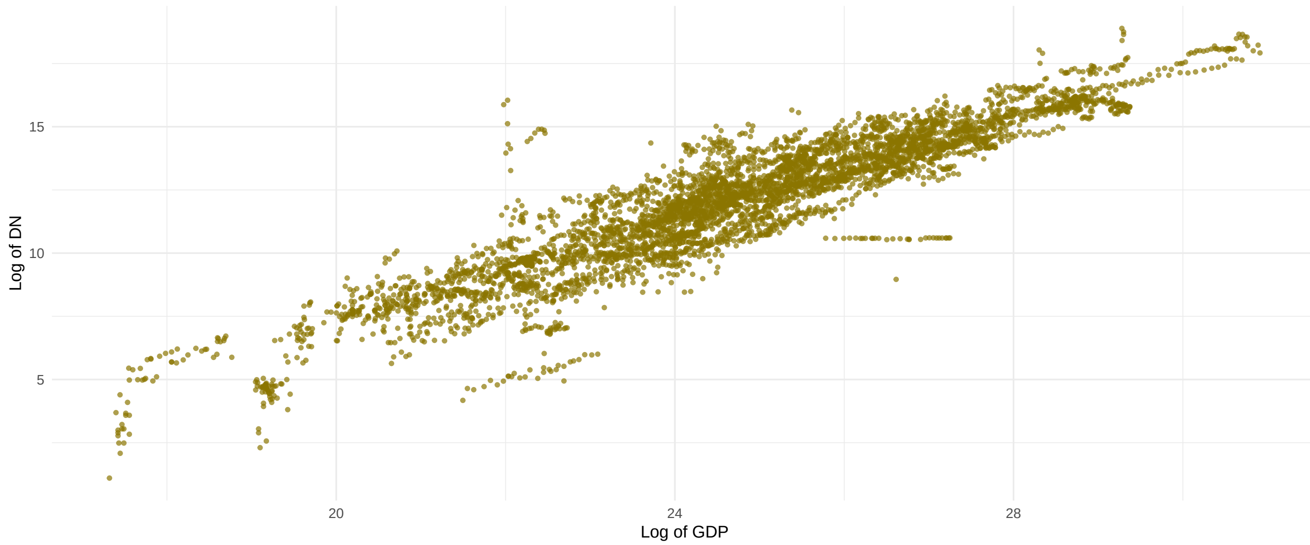

Figure 6: Strong positive correlation between night-time light intensity (Log DN) and GDP (Log GDP), indicating regions with higher GDP levels tend to emit more night-time light

In Figure 7, we observe how this relationship between DN and GDP varies across countries with different statistical capacities. A list of countries categorized by their statistical capacity grades is given in (**tab-grades-countries-latex?**) of the appendix. Countries with higher statistical capacity (graded A and B) exhibit a more tightly clustered and linear relationship, indicating consistent and robust data collection processes. Conversely, countries with lower statistical capacity (graded D and F) show more scatter and variability, suggesting potential discrepancies or weaker data reliability in their national accounts. This shows the intuitive idea that the strength of the DN-GDP relationship can serve as an indicator of the reliability of a country's national statistical systems.

4 Night lights and Population

Larger populations naturally result in higher night-time light emissions due to increased urbanization and economic activity. Figure 1 confirms this with a clear positive relationship between population (log-transformed) and night-time light intensity (Log DN), highlighting how population size contributes to observable brightness from space.

5 NTL and ith Manufacturing Share of GDP

Figure 9 shows the relationship between the manufacturing share of GDP and night-time light intensity (Log DN). The plot shows a weak positive trend for countries with moderate manufacturing shares (up to 20%), where higher manufacturing activity corresponds to slightly higher DN values. However, the relationship becomes less defined for countries with very high or very low manufacturing shares,

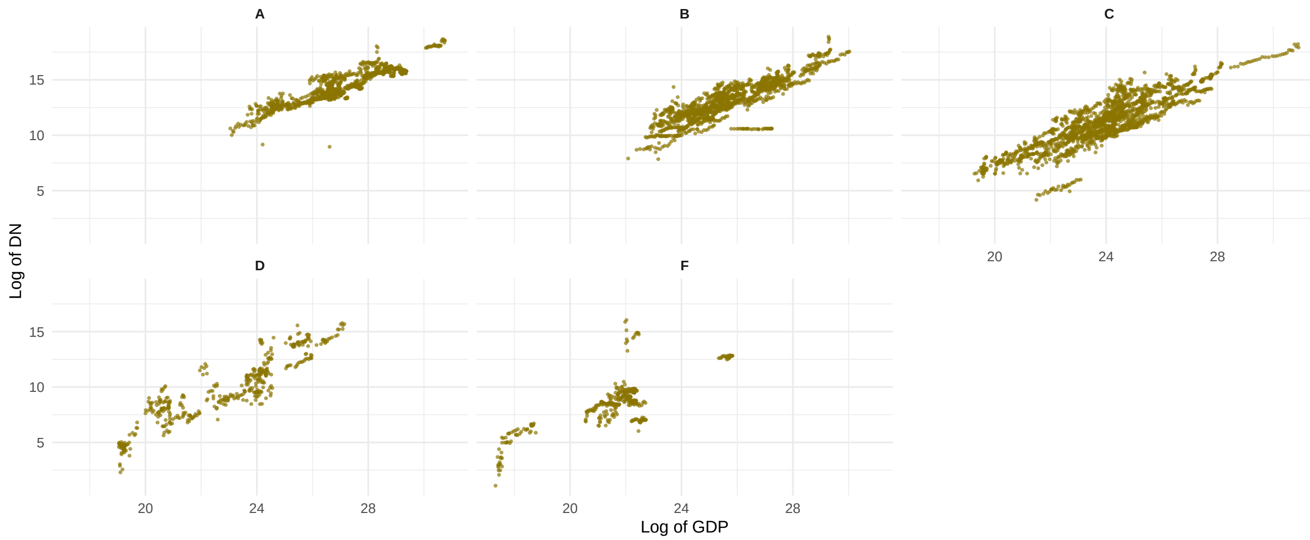

Figure 7: Strength of the correlation between Log DN and Log GDP varies with statistical capacity grades; countries with higher grades (A, B, C) exhibit stronger and more consistent relationships, while lower grades (D, F) show weaker and more dispersed patterns, suggesting the quality of national accounts impacts the NTL-GDP relationship.

Figure 8: Scatterplot of Population versus DN.

suggesting that other economic activities or structural factors might influence night-time light emissions. This indicates that while manufacturing contributes to night-time light, it is not the sole determinant, and its impact may vary across different contexts.

Figure 9: Scatterplot of Manufacturing Share of GDP versus DN.

6 Linear Models

In this section, we present four models to assess the relationship between Night-Time Light (NTL) intensity and various economic indicators, with a particular focus on understanding how NTL correlates with GDP and how this relationship varies across countries with differing levels of statistical capacity. A key challenge in our analysis was the high correlation between GDP, manufacturing share of GDP, and population, as highlighted in the correlation matrix provided in the appendix. This multicollinearity made it impractical to include these variables in the same model without risking inflated standard errors and unreliable coefficients. To address this, we developed separate models for each variable.

The first model examines the relationship between NTL intensity and GDP, incorporating country-specific and year-specific fixed effects. The inclusion of country-specific fixed effects accounts for unobserved factors that differ across countries, such as geographic characteristics, governance structures, or cultural differences. Year-specific fixed effects are included to capture variations over time, such as global economic trends or technological advancements, that may affect the relationship between NTL and GDP.

$$\log(DN_{i,t}) = \beta_0 + \beta_1 \log(GDP_{i,t}) + \alpha_i + \gamma_t + \epsilon_{i,t}$$

- Where:
  - $alpha_i$ Country fixed effects
  - $gamma_t$ Year fixed effects

Building on the first model, the second model investigates how the relationship between NTL and GDP varies across countries with differing statistical capacities. As seen in Figure 1, the scatterplot of GDP and NTL faceted by statistical capacity suggests a weaker correlation in countries with lower statistical capacity. To explore this further, we include an interaction term between GDP and statistical capacity grade, allowing us to examine whether countries with stronger statistical systems exhibit a more consistent and robust relationship between NTL and GDP. The intuition is that higher statistical capacity is associated with better data quality and more stable economic structures, which may enhance the reliability of NTL as a proxy for economic activity. Similar to the first model, we control for year-specific and country-specific fixed effects to account for temporal and cross-country heterogeneity.

$$\log(DN_{i,t}) = \beta_0 + \beta_1 \log(GDP_{i,t}) + \beta_2(\text{Grade}_i) + \beta_3(\log(GDP_{i,t}) \times \text{Grade}_i) + \gamma_t + \epsilon_{i,t}$$

- Where:
  - Interaction term:
  $$\log(\text{GDP}) \times \text{Grade}$$
  - $gamma_t$: Year fixed effects

The third model examines the relationship between NTL intensity and population, while controlling for country and year fixed effects. Population is a key driver of light emissions, particularly in urban areas, and this model isolates its unique contribution to NTL by excluding GDP to address multicollinearity. This approach helps assess whether NTL can serve as a proxy for population, especially in regions where population data may be less reliable, while still accounting for variations across countries and years.

$$\log(DN_{i,t}) = \beta_0 + \beta_1 \log(Population_{i,t}) + \alpha_i + \gamma_t + \epsilon_{i,t}$$

- Where:
  - $alpha_i$: Country fixed effects
  - $gamma_t$: Year fixed effects

The fourth model examines the relationship between NTL intensity and the manufacturing share of GDP, controlling for country and year fixed effects. Manufacturing activity, often concentrated in industrial areas, significantly influences light emissions. By isolating this variable, the model highlights how industrialization shapes NTL patterns, independent of overall GDP, while accounting for country- and time-specific factors.

$$\log(DN_{i,t}) = \beta_0 + \beta_1 \text{Manufacturing Share}_{i,t} + \alpha_i + \gamma_t + \epsilon_{i,t}$$

- Where:
  - $alpha_i$: Country fixed effects
  - $gamma_t$: Year fixed effects

	(1)	(2)	(3)	(4)
(Intercept)	−12.559	−9.441	10.935	10.983
	(1.017)	(0.533)	(0.173)	(0.156)
log(gdp)	0.974	0.871		
	(0.042)	(0.020)		
gradeB		−2.570		
		(0.676)		
gradeC		−4.065		
		(0.600)		
gradeD		−8.978		
		(0.701)		
gradeF		−3.975		
		(0.778)		
log(gdp) × gradeB		0.091		
		(0.026)		
log(gdp) × gradeC		0.144		
		(0.023)		
log(gdp) × gradeD		0.345		
		(0.028)		
log(gdp) × gradeF		0.131		
		(0.033)		
log(population)			0.124	
			(0.034)	
manufacturingsharegdp				0.018
				(0.003)
R2	0.958	0.879	0.949	0.950
R2 Adj.	0.956	0.878	0.947	0.947
Num.Obs.	4967	4967	4466	4466

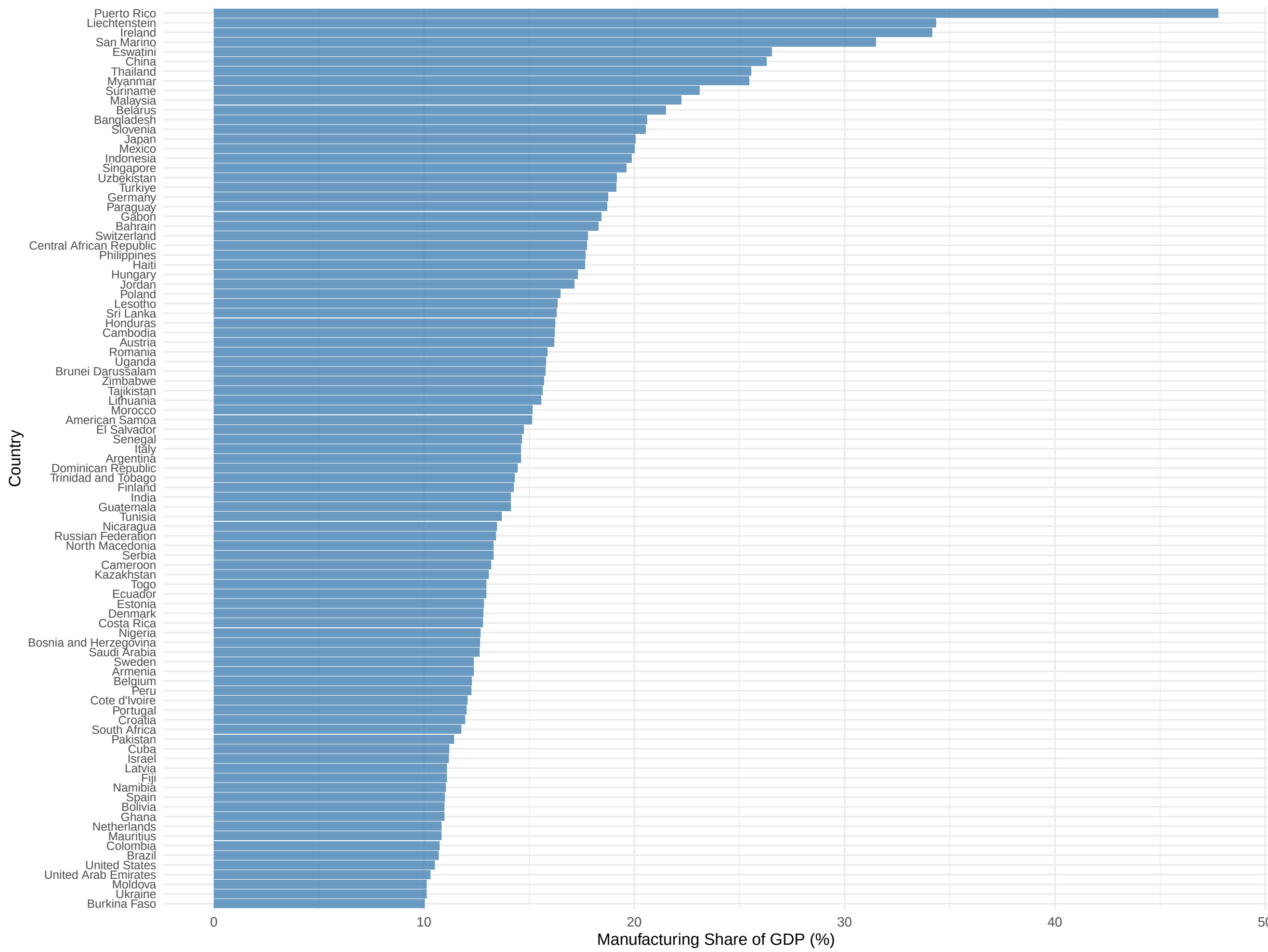

Figure 10: Manufacturing share of GDP for countries in 2020, showing significant variation across nations, with the highest shares observed in Puerto Rico, Liechtenstein, and Ireland. Countries with higher manufacturing shares are expected to exhibit brighter night-time light intensity due to industrial activity.

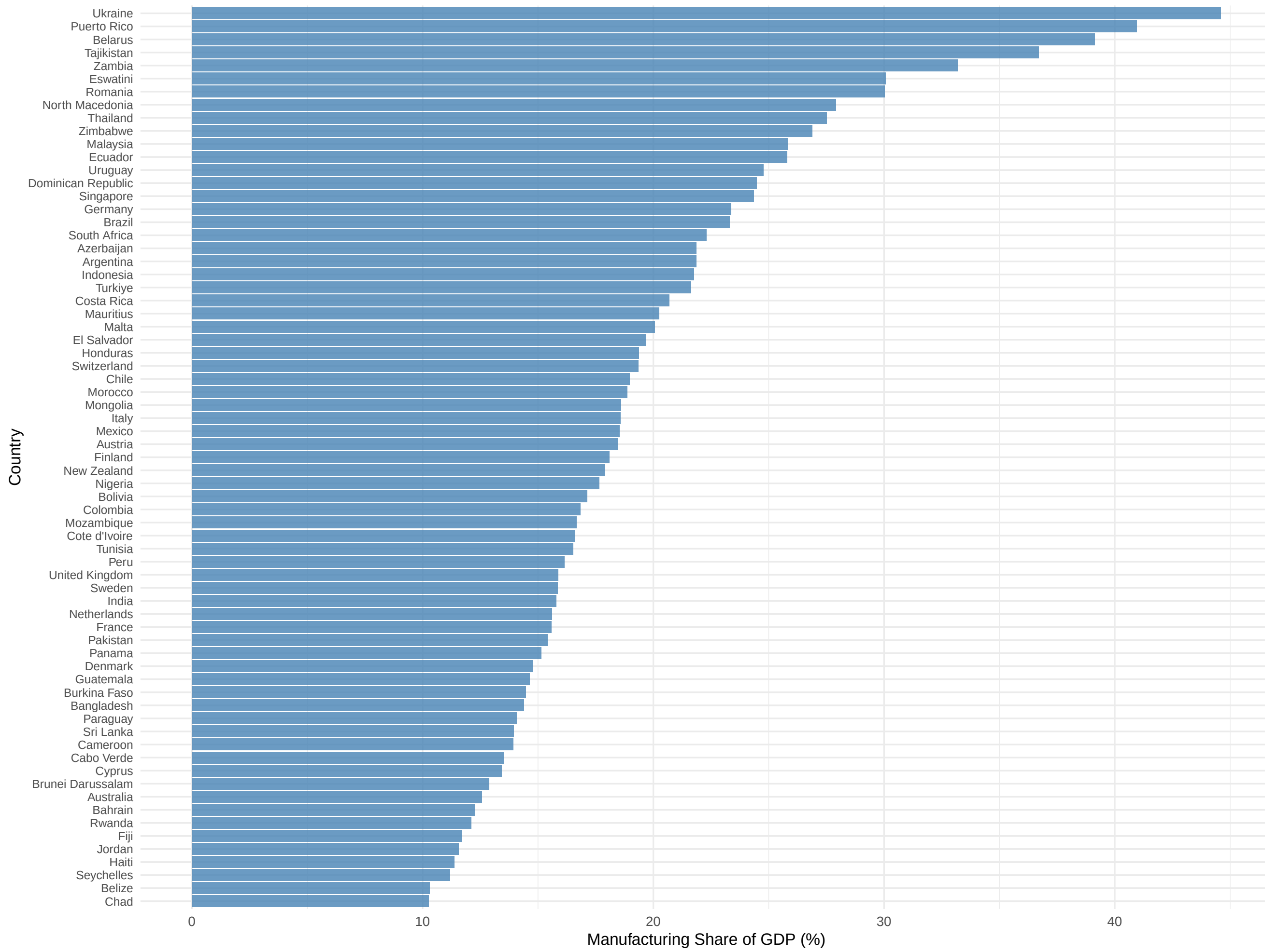

Figure 11: Manufacturing share of GDP for countries in 1992, showing significant variation across nations, with the highest shares observed in Puerto Rico, Ukrain, and Belarus.

Table 3: List of Countries Grouped by Grade.

Grade	Countries
A	Armenia, Australia, Austria, Canada, Chile, Denmark, Estonia, Finland, France, Georgia, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Latvia, Lithuania, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovenia, Spain, Sweden, Switzerland, Turkiye, United Kingdom, United States
B	Albania, Argentina, Azerbaijan, Belarus, Belgium, Bolivia, Brazil, Bulgaria, Colombia, Costa Rica, Croatia, Cyprus, Dominican Republic, Ecuador, El Salvador, Ghana, Guatemala, Iceland, India, Indonesia, Kazakhstan, Luxembourg, Malaysia, Malta, Mauritius, Moldova, Mongolia, Montenegro, Morocco, North Macedonia, Pakistan, Paraguay, Peru, Philippines, Romania, Russian Federation, Rwanda, Senegal, Serbia, Singapore, South Africa, Sri Lanka, Tanzania, Thailand, Tunisia, Uganda, Ukraine, Uruguay
C	Afghanistan, Algeria, Angola, Antigua and Barbuda, Bahrain, Bangladesh, Belize, Benin, Bhutan, Bosnia and Herzegovina, Botswana, Brunei Darussalam, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, China, Cote d'Ivoire, Eswatini, Ethiopia, Fiji, Guinea, Guyana, Honduras, Jamaica, Jordan, Kenya, Kuwait, Lebanon, Lesotho, Liberia, Madagascar, Malawi, Maldives, Mali, Mauritania, Mozambique, Myanmar, Namibia, Nepal, Nicaragua, Niger, Nigeria, Oman, Palau, Panama, Qatar, Samoa, Sao Tome and Principe, Saudi Arabia, Seychelles, Sierra Leone, Suriname, Tajikistan, Timor-Leste, Togo, Tonga, Trinidad and Tobago, United Arab Emirates, Uzbekistan, Zambia, Zimbabwe
D	Chad, Djibouti, Dominica, Equatorial Guinea, Gabon, Guinea-Bissau, Haiti, Iraq, Kiribati, Libya, Marshall Islands, Papua New Guinea, Solomon Islands, Somalia, South Sudan, Sudan, Turkmenistan, Vanuatu
F	American Samoa, Andorra, Aruba, Barbados, Bermuda, British Virgin Islands, Cayman Islands, Central African Republic, Comoros, Cuba, Curacao, Eritrea, Faroe Islands, French Polynesia, Gibraltar, Greenland, Grenada, Guam, Isle of Man, Liechtenstein, Monaco, Nauru, New Caledonia, Northern Mariana Islands, Puerto Rico, San Marino, Turks and Caicos Islands, Tuvalu

7 Model Summary

8 Appendix

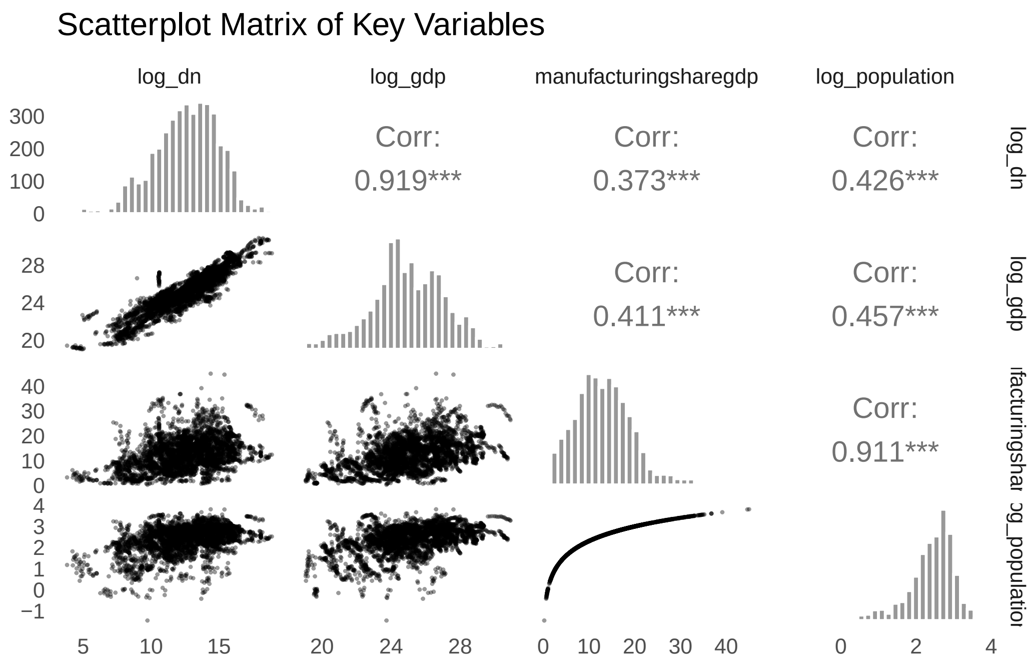

Figure 12: Scatterplot matrix showing pairwise relationships between key variables in the analysis_data dataset.

Reference

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