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ARTICLE

Forecasting Indonesian economic growth using night light

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Abstract

Economic growth is one of the most important indicator that influences economic decisions of private enterprises and governments. Therefore, tracking economic growth in higher frequency would benefit decision makers. One way to verify the official growth number is to use relevant leading indicators for economic growth that are independent from the statistical agency. In this paper, we use the Indonesian nighttime light index to fit historical economic growth of Indonesia. We utilise three different macroeconometric techniques and compare their performances.

Keywords: Night Light; Growth Forecasting; BPS

1. Introduction

GDP and economic growth are arguably the most significant sources of data for the government. Economic growth rate is used as an anchor for various other indicators. It forms the foundation for critical modeling and analysis used by both governments and private investors to make economic decisions and implement policy measures. More importantly, GDP often serves as a performance indicators for the government, which provides an incentive for misreporting growth number (Martínez 2022). It is therefore essential to develop alternative methods to validate and evaluate economic growth data.

One such method lies in the use of nighttime lights as a proxy to nowcast economic growth. The use of satellite imagery, particularly in the form of nighttime lights, has increased in relevance over the last 20 years. Technology has developed to allow for the detection of signals at night coming from common artificial light sources such as streetlights, buildings, and vehicles. This data can then be used to measure human activity, a critical component of economic growth. Nighttime lights growth serves as a good predictor of economic growth at the national and sub-national levels (Henderson, Storeygard, and Weil 2012; Bickenbach et al. 2016; Martínez 2022). Henderson, Storeygard, and Weil (2012) shows how nighttime lights data are able to serve as a better predictor of economic growth than various indicators and proxies in other countries. The fact that nighttime lights data is procured from NASA as an open source ensures full transparency. The data is readily available without any pre-processing or involvement from third parties, meaning it is immune to the fluctuations in perceived credibility that are associated with statistical agencies. The independence from statistical agencies is an important condition that positions nighttime lights well as a leading indicator for GDP growth (Enders 2014).

In this paper, we utilize a raster of monthly nighttime lights data from Indonesia provided by NASA's Black Marble project (Stefanini Vicente and Marty 2023). We then average the data into quarterly, mirroring the GDP data from BPS. We then fit nighttime lights index on real GDP growth using OLS and Autoregressive Distributed Lag (ARDL) model showed the most promising fit. Importantly, we find evidence of a potential structural break post COVID-19. Additionally, we provide a provincial analysis to provide cross-sectional variance. We utilise OLS, provincial fixed effect and two-way fixed effect regression.

This paper aims to test whether nighttime light can be a sole predictor of GDP without adding other variables. Therefore, this paper aims to be as simple as possible. We find that for the national level data, ARDL provides excellent estimators to forecast GDP.

The paper is organised as follows. We discuss the nighttime lights data collection process and exploratory data analysis section two. The methodology development is covered in section three. Section four discusses the model results, followed by a conclusion in section five.

2. Data Collection and Processing

NASA Black Marble (Stefanini Vicente and Marty 2023) is a a daily calibrated, corrected, and validated product suite, curated such that nighttime lights data can be used effectively for scientific observations. The product suite takes full advantage of the capabilities of the Visible Infrared Imaging Radiometer Suite (VIIRS) instrument, which is a component of the Suomi National Polar-orbiting Partnership (NPP) satellite. The instrument consists of 22 spectral bands from the ultra-violet to the infrared, of which the day night band (DNB) in particular is used to observe nighttime lights. The DNB is ultra-sensitive, and can detect very dim light that is several times fainter than daylight. The band covers 0.5–0.9 µm wavelengths (visible green to near-infrared), which is exactly the range of light emitted by common artificial sources like streetlights, buildings, vehicles, and even fishing boats.

While the analysis of nighttime lights has become more popular over the last two decades, a surprisingly few number of studies employ the use of data from VIIRS (Gibson, Olivia, and Boe-Gibson 2020). The new nighttime lights data offers a sharper resolution and higher frequency compared to the previous generation of nighttime lights data. Black Marble's standard science removes cloud-contaminated pixels and and corrects for atmospheric, terrain, vegetation, snow, lunar, and stray light effects on the VIIRS instrument.

The data collection process was performed using the Black Marble Python package developed by the World Bank (Stefanini Vicente and Marty 2023). After mapping and defining Indonesia's coordinates as the region of interest, we were able to use the `blackmarblepy` package to access NASA Black Marble as a xarray dataset. NASA's Black Marble suite offers daily, monthly, and yearly global nighttime lights data. Rasters were able to be created at all three frequency levels. Each xarray dataset contains a nighttime lights tile that is gap-filled and corrected, with a resolution of 500m. Critically, each dataset also contains a main variable representing radiance, a numerical measure of the amount of light energy emitted or reflected from a surface per unit area in a given direction, expressed in watts per square meter per steradian ($W \cdot m^{-2} \cdot sr^{-1}$). It is this measure that allows for nighttime lights to be compared and used as a proxy for GDP growth.

Figure 1 The figure is a visualization of the yearly raster for nighttime lights in Indonesia in 2023. There is a stark contrast between the nighttime lights activity in Java compared to other islands, which is reflective of significant gaps in various socioeconomic indicators between Java and the rest of Indonesia. The stark difference in economic activity between

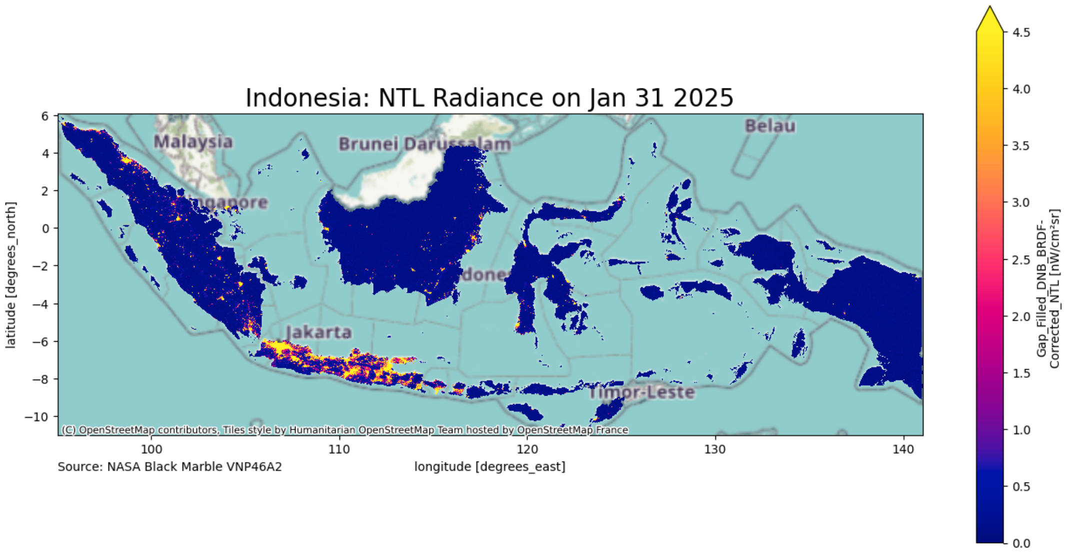

Figure 1. Annual Nighttime Lights in Indonesia, 2023

Java and the rest of Indonesia is well-documented in literature, and is a consequence of the landscape and soil of the island facilitating stronger agricultural yields and population growth.

Black Marble data can also be extracted for multiple time periods. The function will return a raster stack, where each raster band corresponds to a different date. The following code snippet provides examples of getting data across multiple days, for the month of May 2024 in Indonesia. We define a date range using pd.date_range.

Here we can see the fluctuations that exist within a given month, fluctuations that may be difficult to pinpoint from monthly or yearly rasters. One advantage of the flexibility of nighttime lights data is the ability to process it to suit the needs of any kind of time series analysis. In this instance, to facilitate the goal of making a proper comparison between nighttime lights and GDP, both series needed to be expressed on the same unit level. In Indonesia, GDP growth is typically reported in quarterly year-on-year terms. To align the nighttime lights data with this format, multiple steps were needed. First, monthly rasters were extracted from January 2012 to December 2024, covering the full period of available Black Marble nighttime lights data. The data was then saved as a .zip file. The radiance values were also extracted and saved as a separate .csv file.

With the radiance values extracted in a monthly form, the next steps involved transforming the data into quarterly year-on-year terms. Nighttime lights data was aggregated into quarterly terms. The data was then lagged and shifted 1 year back, from which the year-on-year change was able to be calculated.

GDP data was straightforward to collect due to the data being readily available from the BPS website (BPS 2025). Quarterly real GDP is used for the purposes of this study. The GDP series includes data from Q1-2010 to Q2-2025, but we will use Q1-2012 as our starting point in line with the availability of nighttime lights data from NASA Black Marble. We also collets the provincial quarterly real GDP for the provincial-level regression.

Figure 3 shows our two main variables. The left panel is the national real GDP sourced from

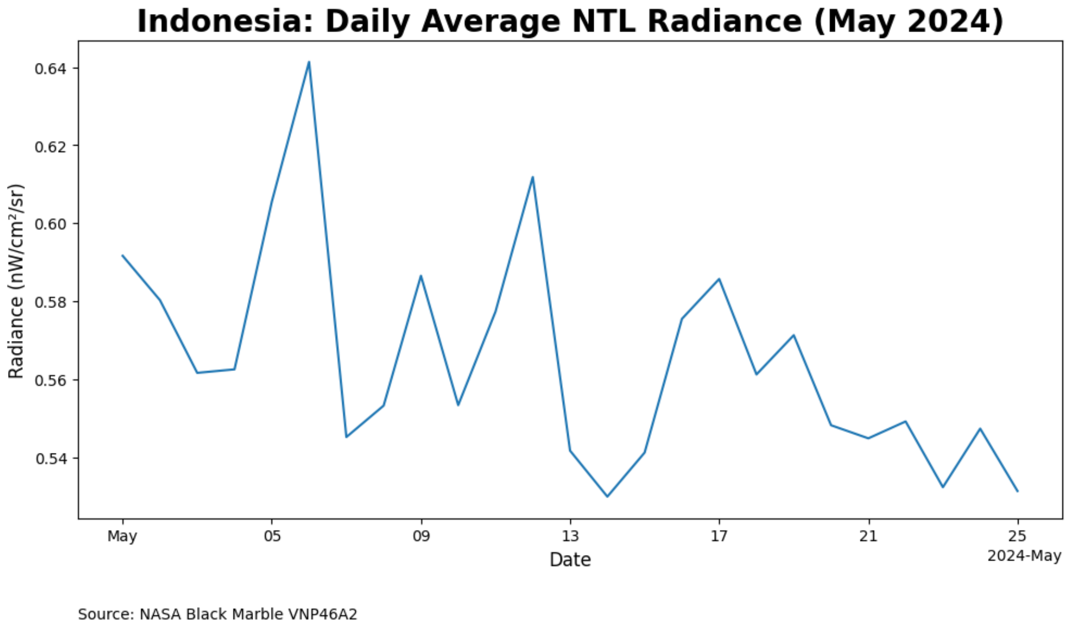

Figure 2. Daily Average Nighttime Light Radiance in Indonesia, May 2024

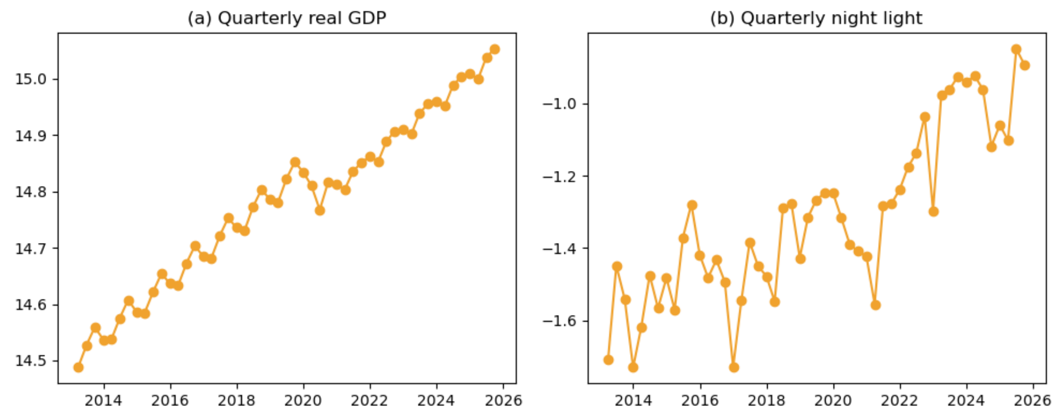

Figure 3. Indonesian economic growth and night light growth

BPS (2025) while the right panel is the calculated night lights we gathered via Black Marble python package. Both seems to follow similar trend. However, night light index doesn't show significant drop during the COVID time, unlike GDP. Additionally, the nightlight index looks to be more stationary before 2022, and then show a positive trend. From the visual inspection, both series seems to be non-stationary.

3. Methodology

For the national level, we do not have any cross-sectional variation. Therefore, techniques that utilise cross-sectional mean cannot be exploited. Multivariate time series techniques, thus, should be the appropriate method.

First, we try a simple OLS:

$$g_t = \alpha_0 + \alpha_1 ntli_t + \epsilon_t$$

where g_t is the log of quarterly GDP at time t, $ntli_t$ is the log quarterly night light index at time t, α_0 is the constant term, α_1 is the coefficient of night light index, and ε_t is the error term. We then examine the error term and see if there is a bias in the residuals. It is reasonable to find autocorrelation in the residual with two time series data. We then use ARDL to take into account the autocorrelation (Enders 2014). We use lags determined by AIC.

$$g_t = \beta_0 + \sum_{i=1}^{p} \beta_i g_{t-i} + \sum_{j=0}^{q} \delta_j ntli_{t-j} + \varepsilon_t$$

In addtion to the above specification, we also test with quarter dummy, Covid dummy (2020-2022) and scarring dummy (2020 onwards).

For the regional level analysis allows for a cross-sectional dimension to be added to the time series data. This allows us to use panel data techniques. We can use provincial fixed effect and two-way fixed effect (TWFE) models.

4. Estimation Results

4.1 National-level analysis

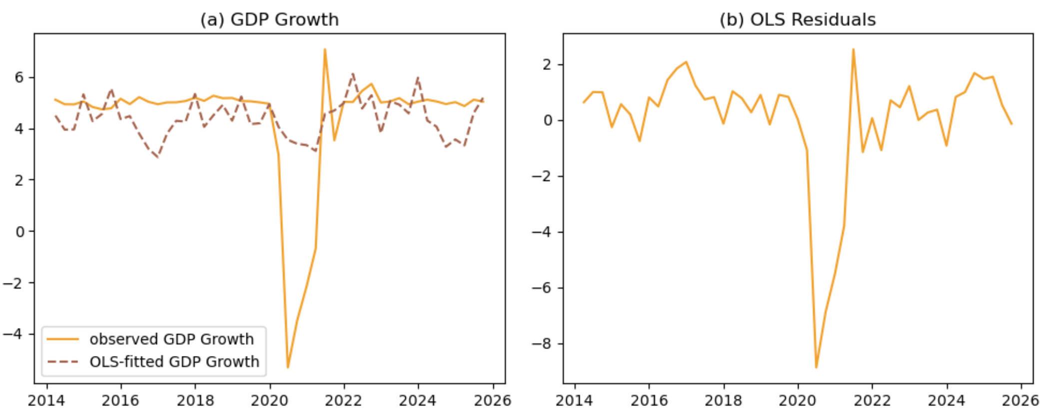

Figure 4. OLS fit and the residuals

Table 1. OLS Regression Results for log real quarterly GDP

Variable	Coefficient
const	15.4878***
	(0.0561)
ntlg	0.5401***
	(0.0407)
Observations	55
R-squared	0.7683
Adj. R-squared	0.7639
F-statistic	175.76

Figure 4 shows the OLS fit and the residuals while Table 1 show the regression result. The nighttime light show a strong correlation to the quarterly GDP. 1% increase in nighttime light index corresponds with 0.57% increase in GDP. However, Figure 4 shows a clear bias on the residuals. The model overpredicts GDP pre-2017 and underpredicts GDP post 2017. This suggest that OLS is not the proper method to model these two series.

Figure 5 shows the ARDL approach. We ran six different specification. The panel (a) shows a baseline model with only log GDP and log nighttime light. Panel (b) adds COVID dummy, that is, a dummy equals one for the year 2020-2022. Panel (c) adds the dummy scar equals 1 for all observation starting 2020. Panel (d) adds quarterly dummy. Panel (e) combines covid dummy with quarterly dummy, while panel (f) use scarring dummy and quarterly dummy. solid line is the actual GDP data while the dashed line illustrate the predicted GDP.

We can see from the Figure 5 that all predicted value follow the actual GDP very well. However, the GDP value predicted by model with scarring, that is, both panel (c) and (f), looks have the smalles discrepancy with the actual data.

Table 2. ARDL Regression Results

Variable	Baseline	+Covid	+Scar	+Quarterly	+Q+C	+Q+S
const	2.2942	2.9864	49.8166***	2.5612*	2.8221*	37.7501***
	(1.5716)	(1.7920)	(5.2152)	(1.3806)	(1.4232)	(4.9545)
trend	0.0008	0.0020	0.0424***	0.0013	0.0020*	0.0321***
	(0.0011)	(0.0014)	(0.0045)	(0.0010)	(0.0011)	(0.0042)
g.L1	0.5393***	0.5947***	-0.7533***	0.6644***	0.6247***	-0.6215***
	(0.1316)	(0.1331)	(0.1196)	(0.1254)	(0.1061)	(0.1025)
g.L2	-0.0804	-0.4507***	-0.9372***	0.1776	0.0812	-0.4841***
	(0.1638)	(0.1561)	(0.0865)	(0.1660)	(0.1338)	(0.1249)
g.L3	0.0036	0.2549	-0.7755***	-0.2861*	-0.1873	-0.5542***
	(0.1682)	(0.1627)	(0.1224)	(0.1691)	(0.1371)	(0.1103)
g.L4	0.3857***	0.3967***	0.0147	0.2708**	0.2861***	0.0454
	(0.1352)	(0.1234)	(0.0766)	(0.1275)	(0.1020)	(0.0631)
covid.L0		-0.0003			-0.0031	
		(0.0098)			(0.0082)	
covid.L1		-0.0482***			-0.0401***	
		(0.0129)			(0.0108)	
covid.L2		0.0370***			0.0318***	
		(0.0136)			(0.0086)	
covid.L3		-0.0272*				
		(0.0147)				
covid.L4		0.0262**				
		(0.0113)				
ntlg.L0	0.0855***	0.0350	0.0119*	0.0571**	0.0312*	0.0115**
	(0.0229)	(0.0227)	(0.0059)	(0.0212)	(0.0183)	(0.0048)
ntlg.L1	0.0033	-0.0350		-0.0275	-0.0372**	

Variable	Baseline	+Covid	+Scar	+Quarterly	+Q+C	+Q+S
	(0.0245)	(0.0209)		(0.0207)	(0.0176)	
ntlg.L2	-0.0460**					
	(0.0224)					
q1.L0						-0.0108***
						(0.0023)
q2.L0				0.0299***	0.0273***	
				(0.0077)	(0.0062)	
q3.L0				0.0293***	0.0278***	0.0079***
				(0.0078)	(0.0062)	(0.0025)
scar.L0			-0.0201***			-0.0204***
			(0.0043)			(0.0035)
scar.L1			-0.0965***			-0.0937***
			(0.0064)			(0.0053)
scar.L2			-0.0621***			-0.0400***
			(0.0127)			(0.0114)
scar.L3			-0.0679***			-0.0308**
			(0.0090)			(0.0115)
scar.L4			-0.0342***			-0.0276***
			(0.0110)			(0.0094)
Observations	51	51	51	51	51	51
AIC	-275.94	-291.52	-408.79	-287.61	-309.81	-428.67
BIC	-256.62	-264.48	-383.68	-266.36	-282.76	-399.69

Table 2 show the estimated parameters of the 6 models. Indeed, models with scarring show the lowest AIC and BIC, which suggests the specifications are the most efficient compared to the other specification. Scarring effect leads to a 2% less of a quarterly GDP. Importantly, the current nighttime light index is significant for all but the covid-dummy specification. The base model shows the strongest correlation, where a higher 1% nighttime light index correlates with a higher 0.0855% GDP. For the scarring specification, the coefficients are 0.0119 and 0.0115 respectively.

To test whether the model can forecast GDP well, we divide the data into training set consisting all observation prior to 2024, and testing set, consists of the rest. The result is illustrated in Figure 6. The solid line is the actual GDP, the dashed line is the predicted GDP using the training set, while the dotted line is the forecast using the testing set. We can see from the Figure 6 that the model with scarring dummy can predict with better fit and smaller error. Notably, the GDP prediction is less sensitive to the nighttime light fluctuation compared to the scarring dummy and the GDP lags. In fact, the nighttime light index is less useful the smaller the training set is used (reflected in the AIC and BIC).

4.2 Regional-level analysis

Figure 7 is a scatterplot of nighttime lights against regional GDP for 34 provinces in Indonesia from 2014Q1 to 2024Q4. The blue dots represent provinces in Java, while the orange dots represent provinces outside Java. The scatterplot shows a positive linear trend between nighttime lights and regional GDP, indicating that higher nighttime light intensity is associated with higher regional GDP. However, there is a noticeable difference between provinces in Java and those outside Java. Provinces in Java tend to have higher nighttime light intensity and higher regional GDP compared to provinces outside Java. The data points for Java are clustered toward the higher end of both axes, while provinces outside Java show greater dispersion, indicating more variation in the relationship between light intensity and GDP possibly due to differences in economic structure or spatial distribution of economic activities.

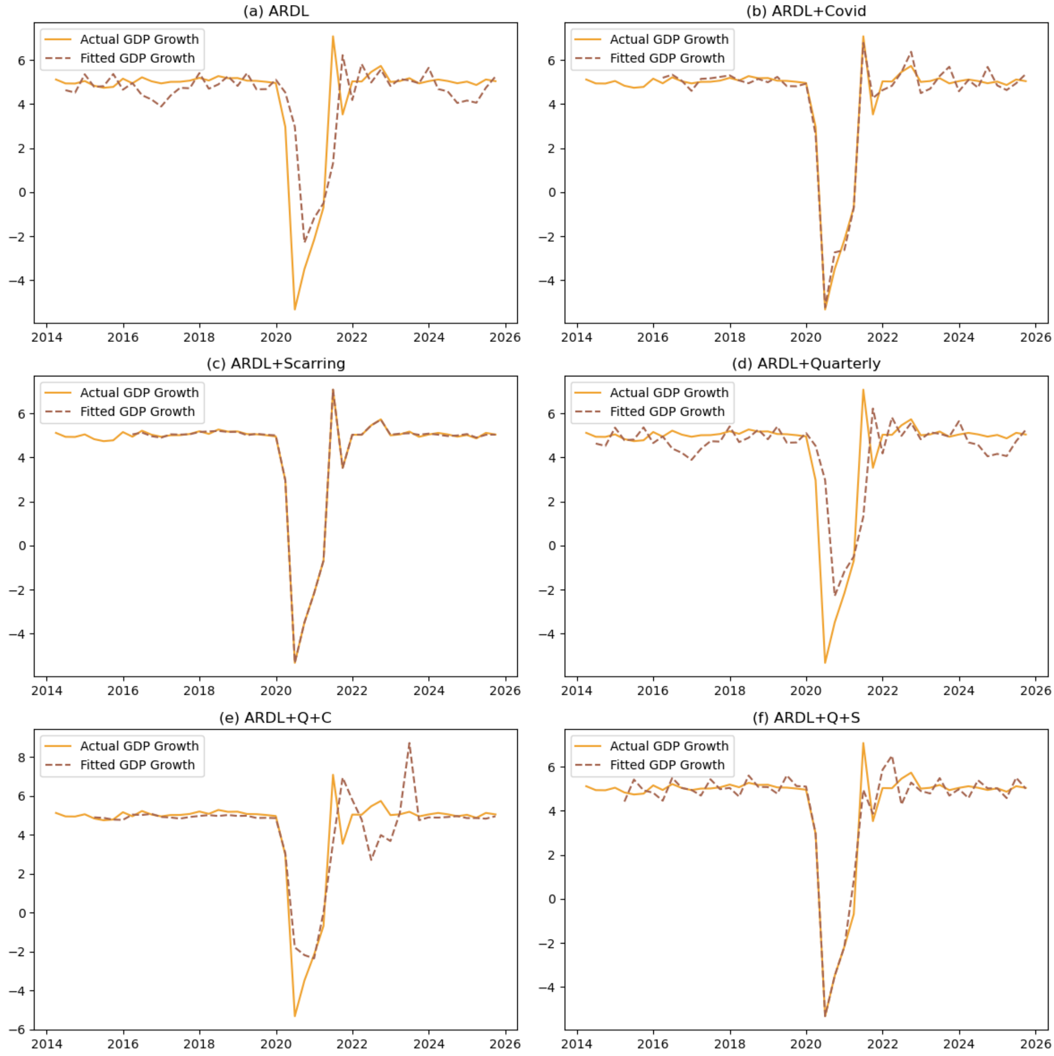

Figure 5. Economic growth prediction with ARDL

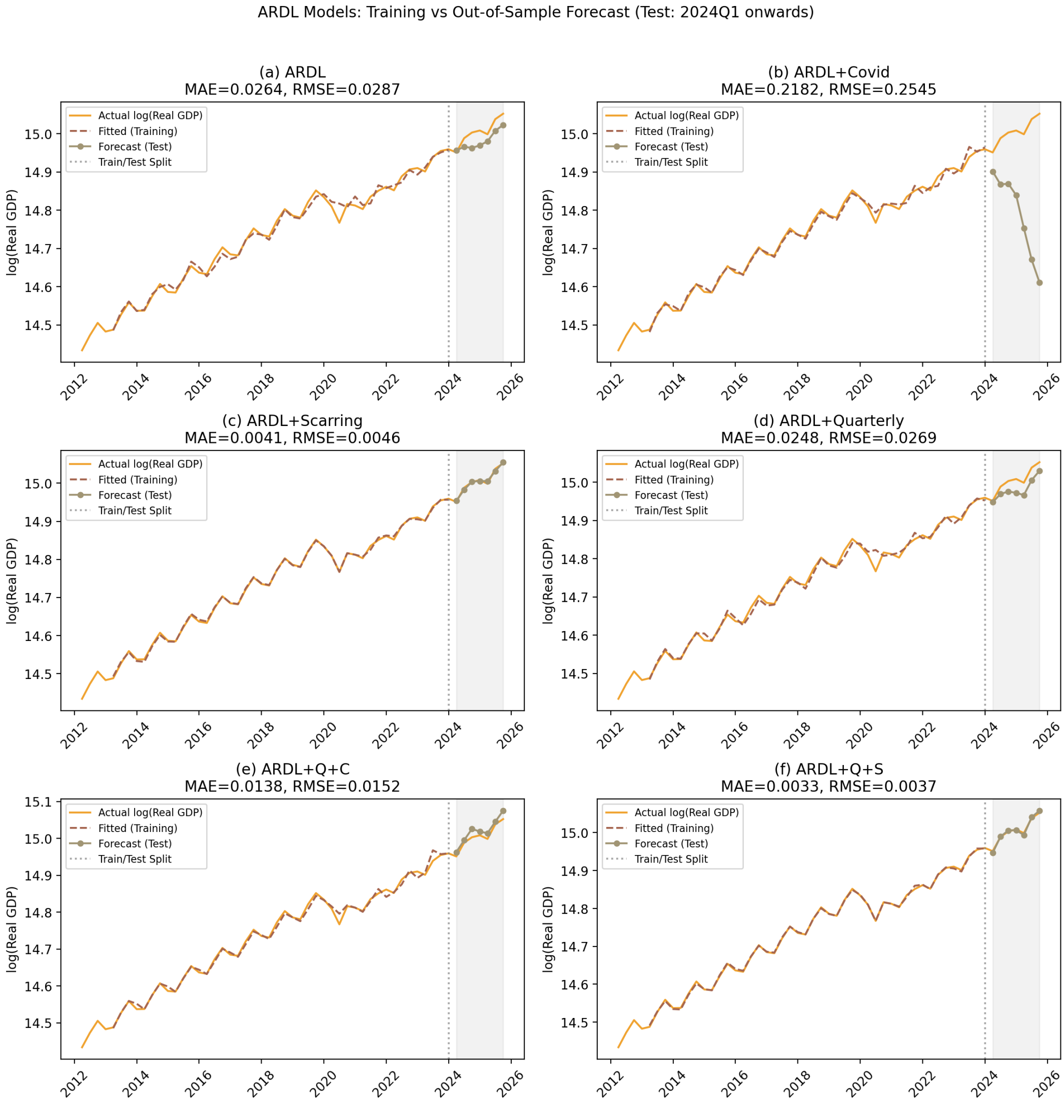

Figure 6. Economic growth prediction with ARDL

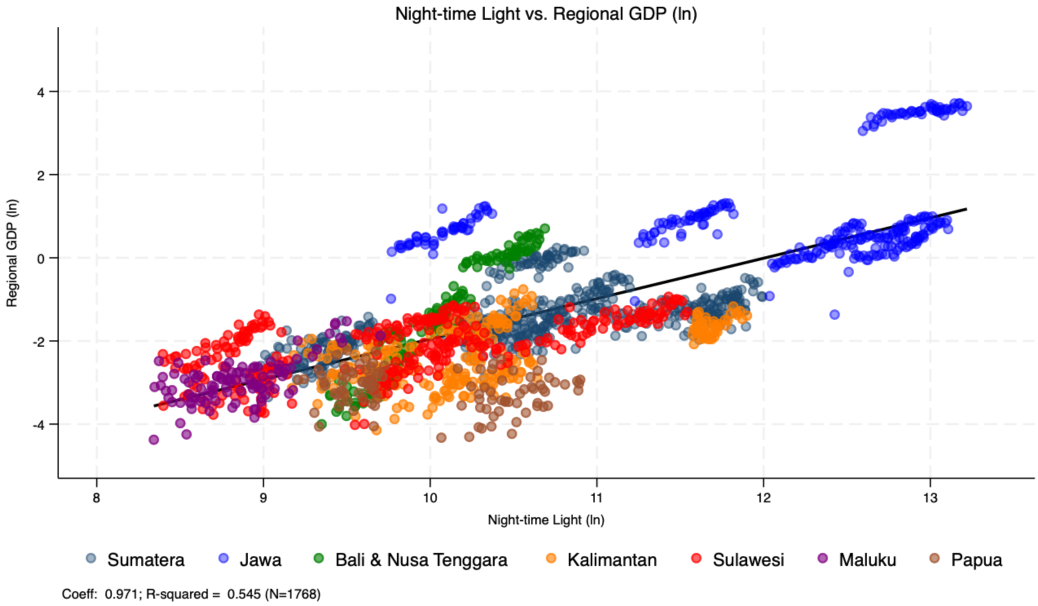

Figure 7. Nighttime-Lights vs. Regional GDP, log

Table 3. Regression results: Provincial GDP and Nighttime Lights

	OLS (1)	OLS (2)	OLS (3)	FE (4)	FE (5)	FE (6)	TWFE (7)	TWFE (8)	TWFE (9)
Nighttime Light, ln	0.561***	0.560***	0.560***	0.317***	0.304***	0.205***	0.0649**	0.0649**	0.0649**
	(0.0119)	(0.0118)	(0.0119)	(0.0344)	(0.0318)	(0.0334)	(0.0250)	(0.0250)	(0.0250)
COVID-19 dummy		Yes			Yes			Yes	
Post pandemic (scarring) dummy			Yes			Yes			Yes
R^2	0.545	0.546	0.545	0.392	0.471	0.529	0.837	0.837	0.837

5. Conclusion

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5.1 Appendix

Appendix A

See imedkrisna.github.io/nitelite/appendix.html

Appendix B

See imedkrisna.github.io/nitelite/appendix_tim.html