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Measuring Quarterly Economic Growth from Outer Space

Robert C. M. Beyer, Yingyao Hu, and Jiaxiong Yao

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Prepared by Robert C. M. Beyer, Yingyao Hu, and Jiaxiong Yao*

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ABSTRACT: This paper presents a novel framework to estimate the elasticity between nighttime lights and quarterly economic activity. The relationship is identified by accounting for varying degrees of measurement errors in nighttime light data across countries. The estimated elasticity is 1.55 for emerging markets and developing economies, ranging from 1.36 to 1.81 across country groups and robust to different model specifications. The paper uses a light-adjusted measure of quarterly economic activity to show that higher levels of development, statistical capacity, and voice and accountability are associated with more precise national accounts data. The elasticity allows quantification of subnational economic impacts. During the COVID-19 pandemic, regions with higher levels of development and population density experienced larger declines in economic activity.

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Author’s E-Mail Address:	rcmbeyer@worldbank.org; yhu@jhu.edu; jyao@imf.org

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I. INTRODUCTION

Satellite-recorded nighttime light data are used extensively as a proxy for economic activity. However, surprisingly little economic analysis employs data from the Visible Infrared Imaging Radiometer Suite (VIIRS).[1] These new nighttime light data, with a better resolution and a higher frequency than the previous generation of data, have the potential to facilitate our understanding of rapid and spatially heterogeneous economic changes, such as those during the COVID-19 pandemic.[2] One reason for the hesitancy to use these data in the economic literature may be the difficulty of converting changes in nighttime light intensity into changes in economic activity. To the best of our knowledge, no properly estimated and widely accepted quarterly elasticity between VIIRS nighttime lights and economic activity exists to date.[3] In this paper, we attempt to fill this gap.

VIIRS nighttime light data are an imprecise measure of man-made lights. Even after aggregating the data to the country level and to quarterly frequency, substantial statistical noise remains. It mainly stems from atmospheric conditions like cloud cover that impact the effective number of observations. For instance, there are only five effective observations at the pixel level on average each month for a median developing country. Equally important, missing observations in the summer months and occasional satellite sensor recalibrations contribute to the noise as well.

In this paper, we provide a novel framework to estimate the elasticity between nighttime light intensity and gross domestic product (GDP) at quarterly frequency, where we use additional information on the varying degrees of noise in nighttime light data to achieve identification. Unlike the previous literature where no information on measurement errors of nighttime lights is utilized, our framework takes them explicitly into account using observational data. Specifically, we use the average number of effective nightly observations in each quarter for each country and show that the elasticity can be precisely estimated in a simple regression equation.

For emerging markets and developing economies (EMDEs), we estimate that a 1 percent change in GDP is associated with a 1.55 percent change in nighttime lights, which we use as the baseline elasticity in this paper. The estimated elasticity varies from 1.36 to 1.81

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[1] A recent survey by Gibson, Olivia, and Boe-Gibson (2020) reviews more than 150 economic studies using nighttime lights and argues that economists seem slower than others to switch to VIIRS data.

[2] For a detailed explanation of the superiority of the VIIRS data see Elvidge and others (2013) and Gibson and others (2021).

[3] The use of nighttime light data from the Defense Meteorological Program Operational Line-Scan System (DMSP-OLS) picked up only after Henderson, Storeygard, and Weil (2012) provided such an elasticity.

with a country's income status and economic structure, deviating not much from the baseline estimate. In addition, our estimates are robust to different model specifications.

Using the baseline elasticity, we construct a new measure of economic activity that is based on the optimal linear combination of light-predicted GDP growth and GDP growth as reported in national accounts. The new measure has optimal weights of 67 percent on light-predicted GDP growth and 33 percent on official GDP growth. This new measure can be especially informative during periods in which official data are less likely to capture economic activity properly, such as during the COVID-19 pandemic.[4] As expected, higher levels of development and statistical capacity reduce both over- and underestimation of GDP. A higher score on voice and accountability, one of the World Bank's Worldwide Governance Indicators, reduces overestimation, in line with a crucial cross-checking function of stakeholders. During COVID-19, the new measure suggests that official statistics may have overstated the negative economic impact for countries with large manufacturing and service sectors. Finally, we employ the spatial granularity of the data and the estimated elasticity to understand subnational heterogeneity of the COVID-19 impact. We find that economic activity declined more in richer districts, likely because services and industrial activity suffered more than agricultural activity. Areas with a higher population density were also hit harder, in line with containment measures being more disruptive for them.

The rest of the paper is organized as follows. Section II discusses related literature. Sections III and IV describe the VIIRS nighttime light data and important stylized facts, respectively. In Section V, we present our approach to estimate the elasticity between nighttime light intensity and GDP growth. Section VI constructs a new measure of economic activity using nighttime lights and compares it with national accounts data. Section VII analyzes the impact of COVID-19 at the subnational level. Section VIII concludes.

II. Related Literature

Nighttime light data from the Defense Meteorological Satellite Program (DMSP), available at annual frequency from 1992 to 2013, have been used extensively in a wide array of economic studies. Among others, the data have proven helpful to monitor economic activity (Henderson and others, 2018; Henderson, Storeygard, and Weil, 2012; Keola, Andersson, and Hall, 2015), to assess the quality of national accounts statistics (Clark, Pinkovskiy, and Sala-i Martin, 2017; Morris and Zhang, 2019; Pinkovskiy and Sala-i-

[4]During the COVID-19 pandemic, official surveys used to estimate GDP could not be conducted in many countries due to stringent lockdown measures.

Martin, 2016a), and to approximate economic activity at small spatial units (Chanda and Kabiraj, 2020; Heger and Neumayer, 2019; Nordhaus and Chen, 2015). A recent survey by Gibson, Olivia, and Boe-Gibson (2020) reviews more than 150 economic studies using nighttime lights and finds that they overwhelmingly use DMSP data.

While more recent VIIRS nighttime light data are understudied in comparison, there are some noticeable exceptions. For example, the higher frequency of these data allowed analysis of India's demonetization in November 2016 (Beyer and others, 2018; Chodorow-Reich and others, 2020). They have also been used to predict GDP in metropolitan statistical areas in the United States (Chen and Nordhaus, 2019) and to analyze the impact of the recent tariff war between the United States and China on China's economy (Chor and Li, 2021). More recently, in response to COVID-19, a growing literature uses VIIRS nighttime lights as a subnational indicator of economic activity at high frequency. Among others, the data have been used to assess the impact of COVID-19 in India (Beyer, Franco-Bedoya, and Galdo, 2021; Beyer, Jain, and Sinha, 2020; Ghosh and others, 2020), China (Elvidge and others, 2020), and Morocco (Roberts, 2021). All these studies struggle to convert changes in VIIRS nighttime lights to changes in economic activity. Chodorow-Reich and others (2020), for example, use an elasticity estimated with annual DMPS-OLS data (Henderson, Storeygard, and Weil, 2012), even though their study uses monthly VIIRS data. Most others are abstaining from the conversion and instead focus on differences between subnational entities (Beyer, Franco-Bedoya, and Galdo, 2021), thwarting quantitative economic conclusions.

So far, to the best of our knowledge, no cross-country study of the quarterly relationship between VIIRS nighttime lights and GDP exists. However, to exploit the full potential of VIIRS data for economic analysis, an elasticity to convert changes in nighttime lights into changes in economic activity is fundamental. This paper fills this important gap. In terms of the econometric framework, it is closely related to the seminal contribution of Henderson, Storeygard, and Weil (2012) and the more recent work of Hu and Yao (2021), which both estimate the annual elasticity between DMSP lights and GDP in a global sample. The elasticity estimated by the former has become the standard elasticity used to date, but its validity for higher-frequency VIIRS data is limited. In addition, identification and estimation of the elasticity depend crucially on assumptions about the signal-to-noise ratios of GDP data. Hu and Yao (2021) address this issue in a non-classical and non-linear measurement error model, allowing for a general relationship between measurement errors of GDP and nighttime light growth, statistical capacity, and geographic locations.[5] In this paper, we develop a novel approach to estimate the quarterly elasticity between VIIRS

[5] In the working paper version, Hu and Yao (2021) also provide an elasticity for VIIRS data. However, different from this paper, they aggregate the data to annual frequency, which leaves very few observations for their estimation and requires estimating the model in levels, which weakens the identification.

nighttime lights and GDP, employing the effective number of nighttime light observations to identify the relationship. The latter provides information to quantify the measurement errors in the lights data, which greatly simplifies the estimation.

In our applications, we construct a light-adjusted measure of economic activity to cross-check official estimates similar to Henderson, Storeygard, and Weil (2012) and Martinez (2021). We check whether measurement errors in the long-term, short-term, and during the COVID-19 pandemic vary systematically with country characteristics. In addition, we study the spatially heterogeneous impact of the pandemic and hence contribute to the large and growing empirical literature on the economic impact of COVID-19.[6]

III. Data

A. Nighttime Lights

Nighttime light data have changed over two different generations of satellites. The first generation of nighttime light data, based on the Operational Linescan Sensor (OLS) onboard the DMSP satellites, covers 1992 to 2013 at annual frequency. The second generation, based on the VIIRS Day Night Band (DNB) onboard the Joint Polar Orbiting Satellite System, covers April 2012 to the present at monthly frequency. Compared with DMSP-OLS, VIIRS nighttime lights have higher resolution and benefit from much improved low light imaging (Elvidge and others, 2013).[7]

This paper focuses on VIIRS nighttime lights at quarterly frequency. To obtain quarterly nighttime lights, we use the monthly version of the cloud-free DNB composites, which excludes data impacted by stray light between April 2012 and December 2020.[8] To obtain nighttime lights at the country level, we take the sum of nighttime lights within each country's administrative boundaries at each point in time.

Some technical details are worth pointing out. First, monthly nighttime light data do not have coverage for certain regions for some months. For example, solar illumination toward the North and South Poles can prevent collection of nighttime light data. Figure 1

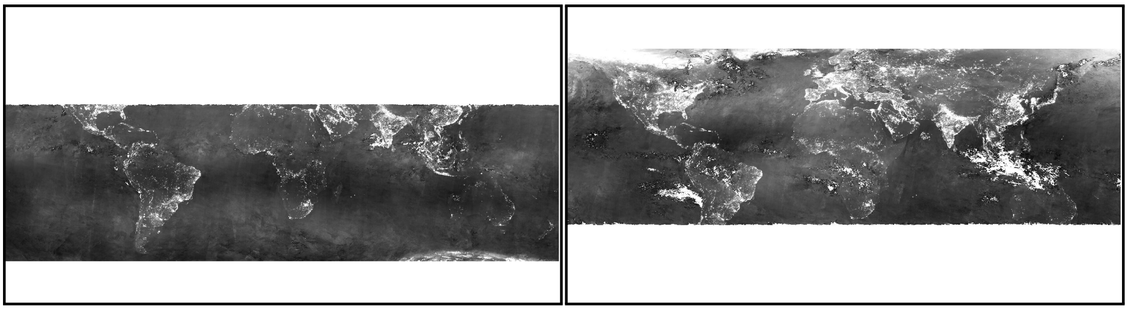
[6]Miguel and Mobarak (2021) provide a good overview of this literature with a focus on low- and middle-income countries.

[7]For more details on different versions of VIIRS nighttime light data, please visit https://eogdata.mines.edu/products/vnl/.

[8]More specifically, we use the vcm configuration which starts from April 2012. The other version of monthly data, vcmsl, starts in January 2014 and we find that it yields similar results for our analysis at the country level. For annual data, we use Annual VNL V2.

illustrates this issue by comparing satellite images of VIIRS nighttime lights in June and December. It shows that no data are available for regions toward the North Pole in June or for regions toward the South Pole in December. Cloud cover in tropical areas can also result in missing monthly observations.[9] Since the data coverage of a country may change drastically from one month to another, a country's nighttime lights are not always directly comparable between months. However, given the seasonal nature of cloud cover and solar illumination, focusing on year-on-year quarterly growth rates alleviates the problem.

Figure 1. VIIRS Nighttime Lights: June versus December



(a) June 2020 **(b) December 2020**

Note. Panels (a) and (b) are satellite images of the same size. Missing data are shown in white. Because of solar illumination in summer months, data are unavailable for regions toward the North Pole in June and for regions toward the South Pole in December.

Second, nighttime light values in low-lit areas make a difference in calculating the sum of nighttime lights at the country level. Due to background noise in the monthly data, low-lit areas may have negative nighttime light values at the pixel level. This happens if low-lit areas are darker than the subtracted background light. Summing the light values of all pixels may even result in negative nighttime lights for small countries in certain months. We hence apply a lower threshold to all nighttime lights in aggregation.[10] Throughout this paper, we use a threshold of zero, implying that we sum over all pixels with a value greater than zero.[11]

Third, satellite sensor recalibration and decay may affect the nighttime lights captured across countries. For example, a recalibration of satellite sensors in the first quarter of 2017 reduced background light and resulted in a worldwide increase in recorded nighttime lights.[12] Countries across the planet all show an increase in nighttime lights, albeit to

[9] See appendix A for further explanation.
[10] Panel (a) in figure B.1 in the appendix shows that the threshold of zero reduces the volatility of the sum of nighttime lights in Sierra Leone and ensures that the sum is always positive.
[11] Threshold values greater than zero yield very similar results.
[12] As shown in Panel (b) in figure B.1 in the appendix. The calibration occurred at 14:18 Coordinated Universal Time on January 12, 2017. For more details, see https://ncc.nesdis.noaa.gov/VIIRS/.

different extents. Since sensor recalibration and decay pertain to all countries, controlling for time and country fixed effects helps to mitigate the issue.[13]

Last but not least, despite all the noise removal, nighttime light growth rates still exhibit large fluctuations. For example, year-on-year quarterly nighttime light growth can exceed 200 percent in some countries in some quarters. Those countries are either very poorly lit because of low electricity access or their nighttime lights are poorly captured because of atmospheric conditions and interference by the sun. A small change in the sum of nighttime lights can then lead to large percentage changes. To mitigate this issue, we winsorize the data by removing the tails of the nighttime light growth distribution. In the following, we report results after removing the top and bottom 5 percent of nighttime light growth rates.[14]

B. GDP Growth and Other Data

GDP Growth, GDP per capita, and Sectoral Shares

For quarterly GDP growth, we use all the available data from the World Economic Outlook database from the International Monetary Fund (IMF), which covers mostly advanced economies. We complement these data with national accounts data for EMDEs compiled by Haver Analytics. We remove the top and bottom 1 percent of GDP growth, effectively limiting the disproportionate influence of very large swings in quarterly growth.

For the level of economic development, we rely on the World Development Indicators (WDI) database from the World Bank and use purchasing power parity-adjusted GDP per capita in constant 2017 international dollars. For the income status of countries, we use the IMF's definition of advanced economies (AEs), emerging markets and middle-income countries (EMs), and low-income developing countries (LIDCs) to divide countries into mutually exclusive groups. For the main analysis, we combine the last two into a single group: emerging market and developing economies (EMDEs).

For the shares of agriculture, manufacturing, and services in each economy, we also rely on the WDI database.

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[13] Since changes in recorded nighttime lights are at the pixel level, there is a stronger increase in lights of larger countries. However, this is of no concern for growth rates of nighttime lights.

[14] We find that not winsorizing nighttime light data at all leads to poor correlation between nighttime light growth and GDP growth. However, winsorizing the tail end of the distribution from 1 to 10 percent yields similar results.

Statistical Capacity and Voice and Accountability

We use the World Bank's Statistical Capacity Indicator, which measures a nationâĂŹs ability to collect, analyze, and disseminate high-quality data about its population and economy. It is a composite score assessing the capacity of a countryâĂŹs statistical system based on the methodologies and data used, as well as the periodicity and timeliness of data releases. It uses publicly available information and country inputs to score countries against 25 criteria.

From the World Bank's Worldwide Governance Indicators, we obtain a measure for voice and accountability. It captures perceptions about citizens' ability to select their government, the extent of freedom of expression and association, as well as the presence of a free media.

Cloud Cover, Subnational Population, and Spatial Aggregation

The Climatic Research Unit at the University of East Anglia provides monthly high-resolution gridded data sets on cloud cover (Harris and others, 2020). For the analysis of elasticities, we take the area-weighted average of cloud cover (CRU TS version 4.03) within each country and across time between 1901-2018.

For our subnational analysis, we use population data from the fourth version of the Gridded Population of the World from the Socioeconomic Data and Applications Center.

Throughout, when aggregating variables by country boundaries, we use the simplified version of Global Administrative Unit Layers 2015 from the Food and Agriculture Organization of the United Nations. When aggregating variables by the first administrative boundaries, we use the Database of Global Administrative Areas version 2.8.

IV. Summary Statistics and Stylized Facts

A. Summary Statistics

Our main analysis focuses on a merged data set of nighttime light growth and GDP growth at quarterly frequency. It covers 117 countries from 2013Q2 to 2020Q4, including 33 advanced economies and 84 EMDEs. Table 1 presents the summary statistics. Across all countries, nighttime lights grew faster than GDP and both nighttime lights and GDP grew on average slower in AEs than in EMDEs. Nighttime light growth is an order of magnitude more volatile than GDP growth, as is clear from the much wider interquartile range of nighttime light growth rates. As can be seen from the 25th percentile, nighttime light growth can be negative even when GDP growth is moderately positive. This is likely a result of the remaining noise in nighttime lights dwarfing the positive contribution from GDP growth to nighttime light growth.

Table 1. Nighttime Lights and GDP Summary Statistics at Quarterly Frequency

	Mean	p10	p25	p50	p75	p90
AEs (33 countries)						
Night light growth	3.0	-15.6	-6.2	2.1	11.3	23.7
GDP growth	1.6	-1.9	0.8	2.1	3.3	4.5
Avg. nightly obs.	25.6	5.9	15.7	27.5	35.1	40.8
EMs (61 countries)						
Night light growth	6.7	-15.7	-4.1	5.0	16.9	33.6
GDP growth	1.9	-3.2	0.7	2.8	4.5	6.1
Avg. nightly obs.	28.5	9.5	17.2	29.6	39.0	46.3
LIDCs (23 countries)						
Night light growth	5.2	-27.3	-13.4	4.3	23.1	40.6
GDP growth	3.7	-1.3	2.5	4.6	6.2	7.4
Avg. nightly obs.	24.9	12.0	16.4	24.6	32.8	38.8
Total (117 countries)						
Night light growth	5.5	-18.3	-6.0	4.1	16.2	32.1
GDP growth	2.1	-2.7	1.0	2.8	4.5	6.2
Avg. nightly obs.	27.2	9.4	16.6	27.9	36.7	44.0

Notes. This table presents summary statistics of year-on-year night light growth and GDP growth between 2013Q2-2020Q4 for different country groups. The mutually exclusive country groups are advanced economies (AEs), emerging markets and middle-income countries (EMs), and low-income developing countries (LIDCs).

Table 1 also provides the average number of nightly observations each quarter that is used to construct the nighttime light data. Nighttime lights of AEs, most of which are located in the northern part of the Earth, are affected by late sunsets in summer months and therefore have on average a lower number of effective observations than EMs. The average AE has about 26 nights of observations each quarter, compared with 29 in an average EM. LIDCs, many of which are situated in tropical areas, also have relatively low numbers of observations due to frequent cloud cover. Even at the 90th percentile, the number of nightly observations is just 39, and hence less than half of a quarter. The variation in the number of nightly observations across countries and over time can be used to quantify the measurement errors in nighttime lights, which allows us to identify the elasticity between nightlight growth and GDP growth.

A country's annual nighttime lights averaged across the monthly data are very strongly correlated with those from alternative annual VIIRS data.[15] However, the correlation of the annual growth rates averaged across the monthly data with the direct annual growth rates is weaker, suggesting that elasticity estimates from annual and monthly data should not be used interchangeably.[16]

B. Cross-Sectional and Temporal Relationships

The recording of nighttime lights is affected by extraterrestrial and atmospheric conditions. As a result, temporal fluctuations in the data can be large, making it problematic to use time-series changes in nighttime lights as a proxy for changes in economic activity directly. However, because the noise is often common to all countries at a point in time, the relationship between nighttime lights and economic activity is strong and relatively stable when the analysis controls for time-specific factors.

Table 2 examines the roles of country- and time-specific factors in the relationship between nighttime light growth and GDP growth. Without any fixed effects, the correlation coefficient of 0.32 is statistically significant only at the 10 percent level, as shown in column (1). With country fixed effects, as shown in column (2), the average temporal correlation between nighttime light growth and GDP growth is not statistically different from zero, suggesting that time-series changes in nighttime lights are a poor proxy for changes in economic activity if time-specific factors are ignored. Columns (3) and (4) show that when the analysis controls for time specific factors, the relationship between nighttime light growth and GDP growth is strong and statistically significant at the 1 percent level.

C. Relationship for Different Country Groups

In table 3, we further examine the relationship between nighttime light growth and GDP growth across different country groups. We group countries by their income status as discussed above.

Table 3 presents the results of regressions of nighttime light growth on GDP growth controlling for country and year fixed effects. Column (1) shows that nighttime light growth

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[15] Separate annual VIIRS data (VNL-V2) provided by Earth Observation Group have undergone an additional filtering and outlier removal processes.

[16] Appendix C provides more details.

Table 2. VIIRS Nighttime Lights: Cross Section and Temporal Relationships

	Night light growth (yoy)			
	(1)	(2)	(3)	(4)
GDP growth (yoy)	0.318*	0.320	0.495***	0.467***
	(0.176)	(0.198)	(0.129)	(0.138)
Country fixed effects	-	Yes	-	Yes
Date fixed effects	-	-	Yes	Yes
Obs	2957	2957	2957	2957
Adjusted R^2	0.00438	0.00543	0.277	0.286

Note. This table presents the regression results of nighttime light growth on GDP growth, incrementally controlling for time and country fixed effects. Throughout, standard errors are clustered by time and in parentheses.yoy=year-over-year. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

is weakly correlated with GDP growth for AEs. Columns (2) and (3) indicate that the relationship is much stronger for EMs and especially LIDCs. Grouping EMs and LIDCs together in column (4), the coefficient on GDP growth is statistically significant at the 1 percent level. Column (5) shows that the coefficient is slightly smaller when estimated using the entire sample, albeit still statistically significant at the same level.

Table 3. VIIRS Nighttime Lights and Economic Growth at Quarterly Frequency

	night light growth (yoy)				
	(1)	(2)	(3)	(4)	(5)
	AE	EM	LIDC	EMDE	All
GDP growth (yoy)	0.266	0.492**	0.710**	0.513***	0.467***
	(0.249)	(0.216)	(0.321)	(0.140)	(0.138)
country fixed effects	Yes	Yes	Yes	Yes	Yes
date fixed effects	Yes	Yes	Yes	Yes	Yes
No. of observations	799	1676	482	2158	2957
No. of countries	33	61	23	84	117
Adjusted R^2	0.217	0.381	0.464	0.353	0.286

Notes. This table presents the regression results of nighttime light growth on GDP growth for different country groups between 2013Q2 and 2020Q4. Mutually exclusive country groups include advanced economies (AEs), emerging markets and middle-income economies (EMs), and low-income developing countries (LIDCs). Emerging markets and developing economies (EMDEs) is the union of EMs and LIDCs. Throughout, standard errors are clustered by date and in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

While table 3 provides insightful information on the relationship between nighttime light growth and GDP growth, the estimated coefficients cannot be used directly as the elasticity of nighttime lights with respect to GDP, because both variables contain measurement errors. In the next section, we develop a framework to estimate the elasticity properly.

V. Elasticity between Nighttime Lights and Economic Activity

The elasticity between nighttime lights and GDP is key to quantify the link between nighttime lights and economic activity. However, both nighttime lights and GDP are measured with errors, complicating the estimation of the elasticity. In this section, we provide a novel framework to identify this elasticity, employing varying measurement errors in nighttime lights across countries.

A. Identification of the Elasticity: A Novel Approach

Let $y_{i,t}$ and $z_{i,t}$ be the measured GDP growth and night light growth of country i in quarter t, respectively. Both $y_{i,t}$ and $z_{i,t}$ are observable. In particular, $z_{i,t}$ is the average of monthly nighttime lights that are in turn predicated on daily observations. While daily observations are not accessible in our data, the number of effective days used to construct monthly observations is known. Let $N_{i,t}$ be the number of effective daily observations of nighttime lights for country i in quarter t, and $z_{i,t,j}$ be the nighttime light growth in day j. Then the relationship between quarterly and daily observations follows:

$$z_{i,t} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} z_{i,t,j}. \tag{1}$$

We assume that $y_{i,t}$ is equal to true GDP growth $y^*_{i,t}$ plus an additive measurement error ε^y_t, and $z_{i,t,j}$ is linearly related to $y^*_{i,t}$ with an additive measurement error $\varepsilon^z_{i,t,j}$:

$$\begin{aligned} y_{i,t} &= y^*_{i,t} + \varepsilon^y_{i,t}, & (2) \\ z_{i,t,j} &= \beta y^*_{i,t} + \varepsilon^z_{i,t,j}. & (3) \end{aligned}$$

β is the elasticity between nighttime lights and true GDP. Daily nighttime light observations $z_{i,t,j}$ can be thought of as a snapshot of economic performance in quarter t, reflecting true GDP growth $y^*_{i,t}$ through the elasticity β. Measurement errors in GDP growth and nighttime light growth are assumed to be independent of true GDP growth and each other.

Let $\sigma^2_{\varepsilon_z}$ be the variance of $\varepsilon^z_{i,t,j}$. Substituting equation (3) into equation (1), we have

$$z_{i,t} = \beta y^*_{i,t} + \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} \varepsilon^z_{i,t,j}. \tag{4}$$

Taking the variance of both sides of equation (4) and the covariance between equations (2) and (4) yields

$$\begin{aligned} \operatorname{var}(z_{i,t}) &= \beta^2 \operatorname{var}(y^*_{i,t}) + \frac{1}{N_{i,t}} \sigma^2_{\varepsilon_z}, & (5) \\ \operatorname{cov}(y_{i,t}, z_{i,t}) &= \beta \operatorname{var}(y^*_{i,t}). & (6) \end{aligned}$$

With equations (5) and (6), we arrive at

$$\operatorname{var}(z_{i,t}) = \beta \operatorname{cov}(y_{i,t}, z_{i,t}) + \sigma^2_{\varepsilon_z} \frac{1}{N_{i,t}}. \tag{7}$$

The relationship in equation (7) is the basis for identification and estimation of elasticity β. The novelty in this approach is that we bring in additional information, the number of nightly observations for each country in each quarter, to achieve identification and precise estimation. Such information is objectively measured, time-varying, and available for all countries.

Henderson, Storeygard, and Weil (2012) use statistical capacity as additional information, but because it is not available for advanced economies, identification must rely on assumptions about the signal-to-noise ratios of the GDP data. Without invoking assumptions about any signal-to-noise ratios, Hu and Yao (2021) use statistical capacity and geographic locations as additional information, allowing for a general relationship between measurement errors of GDP and nighttime light growth, statistical capacity, and geographic location in a non-classical and non-linear measurement error model. Compared with those two approaches, using the number of nightly observations avoids additional assumptions and greatly simplifies the estimation.

To estimate equation (7), we first divide the sample into country-period groups to obtain $\operatorname{var}(z_{i,t})$ and $\operatorname{cov}(y_{i,t}, z_{i,t})$ and then estimate β through a regression based on equation (8). Specifically, for each country i, we divide the observations into K time periods. Within each time period k, we calculate the variance and covariance in equation (8) with quarterly observations as $\sigma^2_{z;i,k}$ and $\sigma^2_{yz;i,k}$, as well as the average $1/N_{i,k}$. We then estimate the following regression to obtain β:

$$\sigma^2_{z;i,k} = \beta \sigma^2_{yz;i,k} + \alpha \frac{1}{N_{i,k}} + \zeta_{i,k}, \tag{8}$$

where β and α are coefficients and $\zeta_{i,k}$ is the residual. In equation (8), $1/N_{i,k}$ is proportional to the variance of measurement errors in nighttime light growth. Other factors, such as the area of a country or its average cloud cover, affect measurement errors in nighttime light growth in a similar way. As a robustness check, we hence also estimate equation (8) by replacing $1/N_{i,k}$ with the area of a country or its average cloud cover.

B. Baseline Estimates

First, we remove country and time fixed effects by regressing nighttime light growth and GDP growth on country and time dummies, respectively. Working with the residuals, we use two years of data for each country to calculate the variances and covariances. The weak correlation between nighttime light growth and GDP growth in advanced economies would reduce the efficiency of our estimation, so that we only include EMDEs.[17] In addition to the number of valid observations each quarter, we consider the area of each country and the annual average cloud cover as additional control variables. Both are likely to affect the variance of nighttime light growth, since larger and cloudier countries tend to have larger noise in nighttime light growth (see figure D.1 in the appendix).

Table 4 presents the estimation results of elasticity regression (8). Columns (2)-(5) show that the elasticity is around 1.55. The coefficient of $1/N$ is statistically significant at the 1 percent level in column (2) and at the 10 percent level in column (5), supporting our identification assumption with the number of effective observations capturing cross-country variability in the variance of nighttime light growth. The coefficients of area and cloud cover are also statistically significant at the 1 percent level when included alone, indicating that they also affect the noise in nighttime light growth. Across the different specifications, the estimated elasticity stays nearly the same, varying from 1.51 to 1.60 when the controls are included separately and rising to 1.64 when they are included together. The elasticity is hence higher than suggested by the simple regression presented in table 3. It is also higher than the central unity estimate in Henderson, Storeygard, and Weil (2012) and the 1.3 estimated in Hu and Yao (2021), both of which use annual DMSP nighttime

[17]Nighttime lights are also a more important source of information in EMDEs, since they typically have less accurate national accounts and less subnational measures of GDP.

light data from 1992.[18] However, our estimate is somewhat below the implied elasticity between VIIRS nighttime lights and GDP per capita in China, which Chor and Li (2021) estimate to be 2.1.

Table 4. Elasticities between Nighttime Lights and GDP

	Variance of night light growth: var(z)				
	(1)	(2)	(3)	(4)	(5)
cov(y,z)	1.46***	1.55***	1.51***	1.60***	1.64***
	(0.55)	(0.54)	(0.54)	(0.54)	(0.54)
$1/N$		522.0***			341.4*
		(139.8)			(198.6)
Area			0.12***		0.026
			(0.045)		(0.061)
Cloud cover				4.32***	3.47***
				(1.14)	(1.19)
Obs	327	327	327	319	319
Adjusted R^2	0.018	0.056	0.036	0.058	0.074

Note. This table presents the results of regression (8) and its variants with other covariates. The first row represents estimates of the elasticity between nighttime lights and GDP. The sample includes 84 emerging markets and development economies between 2013Q2 and 2020Q4. Each time period that is used to estimate the variances and covariances covers two years, i.e., 2013-14, 2015-16, 2017-18, and 2019-20. Throughout, standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We choose the elasticity estimate of 1.55 in column (2) as our baseline for subsequent analysis since $1/N$ varies across countries and over time and contains more observations than area and cloud cover. However, the difference between the estimated elasticities in columns (2)-(4) is small compared with their standard errors. In practice, one could use any one of them.

C. Robustness

Our estimated elasticity is very similar whether differences in the variance in nighttime light growth are explained by the number of effective observations, the average cloud cover of countries, or by their country size. In this section, we test the model's robustness to data winsorization, estimation choices, and the inclusion of different country groups.

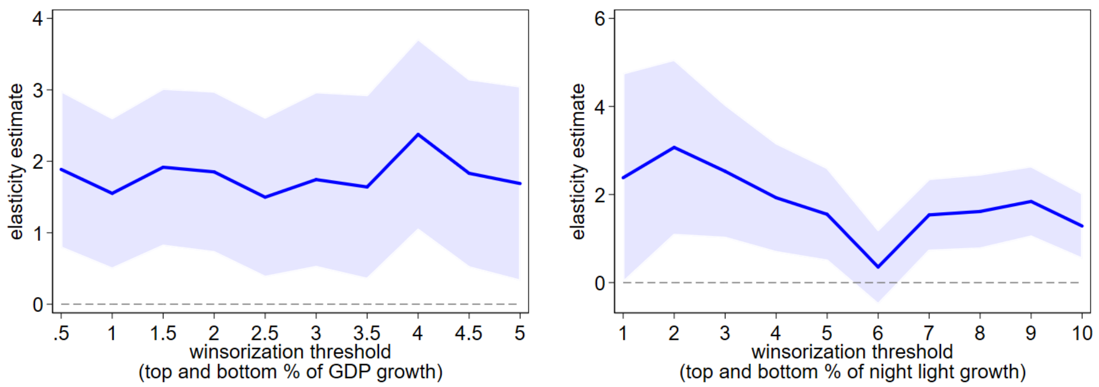
[18]However, it is within the range of elasticites presented in table 5 of Henderson, Storeygard, and Weil (2012).

Data Winsorization

As mentioned in section III, we winsorized the data by removing the top and bottom 5 percent of the nighttime light growth distribution as well as the top and bottom 1 percent of the GDP growth distribution. Such winsorization is useful because growth rates at the extreme ends have disproportionate influence on the estimated relationship. Since nighttime light growth is much more volatile than GDP growth, we chose a higher truncation threshold for nighttime light growth than for GDP growth.

Figure 2 shows how the removal of the extreme ends of the nighttime light growth and GDP growth distributions affects the estimated relationship. In line with the baseline, we exclude the top and bottom 5 percent of the nighttime light growth when focusing on the role of extreme GDP growth. Equivalently, to investigate the impact from varying the threshold for light, we exclude the top and bottom 1 percent of GDP growth.

Figure 2. Elasticity Estimates with Various Choices of Winsorization



(a) By GDP growth **(b) By nighttime light growth**

Note This figure presents the results of regression (8) with various winsorization of GDP and nighttime light data. In panel (a), the sample excludes the extreme ends of the GDP growth distribution with increasingly higher thresholds, with the top and bottom 5 percent of nighttime light growth distribution excluded throughout. In panel (b), the sample excludes the extreme ends of the night light growth distribution with increasingly higher thresholds, with the top and bottom 1 percent of GDP growth distribution excluded throughout. Blue lines are point estimates and blue bands are 95 percent confidence intervals.

Panel (a) shows that winsorization of GDP growth has only a very small impact on the estimated elasticity, which fluctuates around 1.74, with our baseline choice resulting in an elasticity closer to the lower bound. For nighttime light growth, winsorization plays a much larger role. The elasticity and its standard error are considerably higher for lower thresholds, but stabilizes around 1.5 for higher ones. Summarizing, data winsorization impacts the results but our baseline results are relatively robust to changing the threshold for GDP growth in any direction and for excluding more observations for nighttime light growth.[19]

Alternative Estimation Strategy

In equation (8), we observe that for each country i, there is a trade-off between the number of observations used to estimate $\text{var}(z_{i,t})$ and $\text{cov}(y_{i,t}, z_{i,t})$ and the number of variances and covariances to estimate β. Since we have almost eight years of quarterly data, using two years of data to calculate the variances and covariances leaves four observations from each country to estimate β, as in the baseline presented in section V.B.

Alternatively, more observations can be used to obtain more accurate variances and covariances, but only at the expense of having fewer observations to estimate β. When three years of data are used to estimate the variances and covariances, three-quarters of the observations remain. In that case, the elasticity loses statistical significance but remains statistically significant at the 5 percent level. When four years of data are used, only half of the observations remain and the coefficient is not significant even at the 10 percent level.[20] However, the elasticity remains very similar in terms of magnitude, which is reassuring.

Heterogeneity across Countries

Next, we investigate whether the elasticity depends on the income level and the economic structure. To do so, we estimate the elasticity separately for countries with below and above median GDP per capita, share of agriculture, share of industry, and share of services. Table 5 reports the different elasticity estimates, ranging from 1.36 to 1.81. First and foremost, we only find modest differences between the relationships among the different groups. However, with fewer observations in the different groups, the elasticity is not statistically significant even at the 10 percent level in some cases. Somewhat surprisingly, the elasticity is statistically significant at the 5 percent level for the poorer countries with a higher share of agriculture (and a lower share of industry and services). This could reflect the better measurement of nighttime lights in low-lit areas with VIIRS compared with DMSP-OLS sensors and suggests that VIIRS data offer great opportunities for economic analysis even in the least developed countries and regions.

[19] Table E.1 in the appendix provides detailed estimates with various winsorization thresholds.
[20] See table F.1 in the appendix, which replicates table 4 with alternative groupings.

Table 5. Elasticities between Nighttime Lights and GDP, by Economic Structure

	Variance of night light growth: var(z)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	EMDEs	GDP per capita		Agriculture share		Industry share		Services share	
		Below	Above	Below	Above	Below	Above	Below	Above
cov(y,z)	1.55***	1.52**	1.61	1.45	1.52**	1.66**	1.36	1.36**	1.81
	(0.54)	(0.62)	(1.21)	(1.09)	(0.64)	(0.70)	(0.86)	(0.61)	(1.49)
$1/N$	522.0***	1056.0	565.0***	531.3***	1049.4	1390.2	513.6***	2168.0***	526.8***
	(139.8)	(990.8)	(136.5)	(136.7)	(925.9)	(972.9)	(136.7)	(750.0)	(119.8)
Obs	327	173	151	161	166	169	158	175	152
Adjusted R^2	0.056	0.029	0.097	0.081	0.029	0.031	0.082	0.058	0.11

Note. This table presents the results of regression (8) by economic structure. The first row represents estimates of the elasticity between nighttime lights and GDP. The sample includes 84 EMDEs between 2013Q2 and 2020Q4. Column (1) replicates column (2) in table 4 as our baseline estimate of elasticity. Columns (2)-(9) consider grouping countries based on their GDP per capita and sector share relative to the median of the sample. For each variable, below (above) indicates below (above) the median of that variable in the sample. For example, column (2) includes countries whose GDP per capita is below the median. Each time period used to estimate the variances and covariances covers two years, 2013-14, 2015-16, 2017-18, and 2019-20. Throughout, standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

VI. Combining Nighttime Lights and National Accounts

GDP growth as reported in national accounts may not always be an accurate measure of economic activity, in particular if statistical capacity is weak or if there is political pressure on statistical authorities. These concerns may be aggravated during periods of large economic disruptions. Since the measurement error in nighttime lights is plausibly independent of the measurement error in GDP, we can use nighttime lights as an independent benchmark to assess existing measures of economic activity (Aruoba and others, 2016; Pinkovskiy and Sala-i-Martin, 2016a; Pinkovskiy and Sala-i Martin, 2016b). Nighttime light adjusted GDP, a measure that optimally combines GDP growth from national accounts with GDP growth predicted by nighttime lights, provides a complementary view of changes in economic activity.

A. A Light-Adjusted GDP Measure

Let $\tilde{y}$ be a linear prediction of GDP growth by nighttime light growth,

$$\tilde{y}_{i,t} = \gamma z_{i,t} + \gamma_d d_t + \gamma_c c_i, \tag{9}$$

where d_t's are temporal changes in nighttime light growth common to all countries and c_i's are time-invariant, country-specific factors that affect nighttime light growth. We consider a linear combination of y and $\tilde{y}$ as a new measure of GDP growth,[21]

$$\bar{y} = (1-\lambda)y + \lambda\tilde{y}, \tag{10}$$

where λ is the weight on nighttime lighted-predicted GDP growth.

The expected mean squared prediction error of the new measure follows:

$$\begin{aligned}
E(\bar{y}-y^*)^2 &= E\left[(1-\lambda)(y-y^*) + \lambda(\tilde{y}-y^*)\right]^2 \\
&= (1-\lambda)^2\text{var}(\varepsilon^y) + \lambda^2\text{var}(\tilde{y}-y^*) \\
&= (1-\lambda)^2\text{var}(\varepsilon^y) + \lambda^2\text{var}(\gamma(\beta y^* + \varepsilon^z) - y^*) \\
&= (1-\lambda)^2\text{var}(\varepsilon^y) + \lambda^2\left[(\gamma\beta - 1)^2\text{var}(y^*) + \gamma^2\text{var}(\varepsilon^z)\right].
\end{aligned}$$

The optimal linear combination that minimizes the expected mean squared prediction error therefore has the following weight:

$$\lambda^* = \frac{\text{var}(\varepsilon^y)}{\text{var}(\varepsilon^y) + (\gamma\beta - 1)^2\text{var}(y^*) + \gamma^2\text{var}(\varepsilon^z)} \tag{11}$$

Empirically, since we have identified β already, the remaining terms can be computed as follows:

$$\begin{aligned}
\text{var}(y^*) &= \text{cov}(y,z)/\beta &(12)\\
\text{var}(\varepsilon^y) &= \text{var}(y) - \text{var}(y^*) &(13)\\
\text{var}(\varepsilon^z) &= \text{var}(z) - \beta^2\text{var}(y^*). &(14)
\end{aligned}$$

For the estimate of β, we use the result in column (2) in table 4. Regression equation (9) yields a point estimate of γ of 0.0157, with t-statistic 4.01 and significance at the 1 percent level.[22] We estimate $\text{var}(z)$, $\text{var}(y)$, and $\text{cov}(y,z)$ directly from the sample. With those estimates, we arrive at an optimal weight of 0.67. The first row in table 6 presents from left to right the intermediate calculation results of equations (12)-(14). The second row presents some useful statistics. Notably, the majority of the variance of nighttime light growth can be attributed to noise.

[21] For ease of presentation and without loss of clarity, we have omitted the subscripts.

[22] The regression table and further explanation are included in appendix G.

Table 6. Optimal Weight on Nighttime Lighted-Predicted GDP Growth

	β	γ	cov(y,z)	var(y^*)	var(y)	var(ε^y)	var(z)	var(ε^z)
Point estimate	1.55	0.0157	4.05	2.62	7.90	5.29	259	252

	optimal weight	var(y) decomposition		var(z) decomposition	
		signal	noise	Signal	Noise
Point estimate	0.67	33%	67%	2%	98%

Note. This table presents detailed calculations of the optimal weight based on equation (11). The sample includes 84 EMDEs between 2013Q2 and 2020Q4. β is estimated in column (2) in table 4 and γ in column (4) in table G.1.

B. Shedding Light on National Accounts

Long-Run Differences between National Accounts and Nighttime Lights

Following Henderson, Storeygard, and Weil (2012), we start by analyzing long-run differences between GDP growth as reported in national accounts and adjusted GDP growth incorporating information from nighttime light growth. To do so, let y_i^L and z_i^L be long-run average official GDP growth and nighttime light growth, respectively, between 2012Q4 and 2020Q4 for country i. We first construct a linear prediction of long-run average GDP growth by long-run average nighttime light growth:

$$\tilde{y}_i^L = \gamma^L z_i^L, \tag{15}$$

Analogous to equation (10), we then construct a new measure of long-run GDP growth using the predicted long-run average GDP growth from equation (15), $\tilde{y}_i^L$, and the optimal weight obtained in table 6:

$$\bar{y}_i^L = (1-\lambda)y_i^L + \lambda \tilde{y}_i^L. \tag{16}$$

To examine the difference between our new measure and the official measure of long-run GDP growth and the factors behind such discrepancies, we conduct the following regressions:

$$\bar{y}_i^L - y_i^L = x_i^L \beta^L + \xi_i^L. \tag{17}$$

where $\bar{y}_i^L - y_i^L$ is the difference between the new and official measures. A positive (negative) difference implies that nighttime light growth suggests an underestimation (overestimation) by the official data. We also consider the absolute difference, $|\bar{y}_i^L - y_i^L|$, which indicates the overall discrepancy. x_i^L is a vector of covariates that may explain the discrepancy, including economic, political, and statistical factors. Specifically, we consider income, statistical capacity, voice and accountability, and the structure of the economy.[23] ξ_i^L is the residual.

We first analyze absolute differences. As column (1) in table 7 shows, more developed countries tend to have smaller long-run differences (statistically significant at the 10 percent level). Higher voice and accountability reduces the difference as well (statistically significant at the 10 percent level). This result is very much in line with recent findings that the elasticity between nighttime lights and GDP is higher in more authoritarian regimes and especially with weak constraints on GDP exaggeration (Martinez, 2021).

Comparing two countries can provide some intuition for these regression results. For example, since Lesotho is less developed than South Africa and scores lower in terms of voice and accountability, the results suggest a larger deviation of Lesotho's reported and nighttime light-adjusted GDP growth compared to South Africa. Based on the regression coefficients and underlying data, the predicted difference between the two countries is 0.74 percentage points (0.19 from voice and accountability and 0.55 from the level of development), which is very close to the actual difference between them (0.63 percentage points).

Next, we analyze countries separately depending on whether nighttime light growth suggests an under- or overestimation of GDP in the long run. For the former, we do not find meaningful relationships with the explanatory variables, which hence cannot explain whether countries underestimate a lot or a little. By contrast, larger overestimation is associated with a lower level of development, lower statistical capacity, and lower voice and accountability (all statistically significant at the 10 percent level).

Short-run Differences between National Accounts and Nighttime Lights

Next, we abstract from long-run differences and focus on short-run differences. While systematic differences between official GDP growth and nighttime light-adjusted GDP growth are revealed in the long run, short-run differences can provide insights into GDP growth measurement errors in extraordinary episodes when official measures might be inadequate, such as during conflicts, social unrest, and epidemics. By allowing for country-specific intercepts in equation (9), long-term differences are filtered out. The nighttime light-adjusted GDP measure fluctuates around GDP as measured in the national accounts,

[23] A table of summary statistics is included in appendix H.

Table 7. Systematic Difference between New and Official Growth Measures

	Absolute difference (1)	Underestimation (2) difference>0	Overestimation (3) difference<0
(log) GDP per capita	-0.36*	-0.22	0.54*
	(0.21)	(0.30)	(0.30)
Statistical capacity	-0.0029	0.00093	0.032*
	(0.0094)	(0.013)	(0.018)
Voice and accountability	-0.33*	-0.32	0.44*
	(0.18)	(0.28)	(0.22)
Agriculture share	-0.019	-0.0077	0.062
	(0.027)	(0.048)	(0.039)
Industry share	-0.0080	-0.011	-0.016
	(0.021)	(0.039)	(0.025)
Service share	0.0091	0.042	0.018
	(0.025)	(0.046)	(0.029)
Constant	4.58*	1.21	-9.79**
	(2.71)	(4.75)	(4.05)
Obs (number of countries)	76	32	44
Adjusted R^2	0.042	-0.044	0.20

Note. The sample includes 76 EMDEs between 2013Q2 and 2020Q4. Throughout, standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

but there are no differences on average over the estimation period. Large absolute differences between the two imply both strong under- and overestimation of GDP.

Our light-adjusted measure derived from equation (10) may be especially insightful during episodes with large economic disruptions. For example, lockdown measures during COVID-19 severely disrupted economic activity in 2020. All countries struggled to capture the extent of the disruption with official statistics, especially those with large informal service sectors. To understand which factors contribute to larger measurement errors in normal times and during COVID-19, we estimate the following regression model:

$$\bar{y}_{i,t} - y_{i,t} = x_{i,t}\beta_0^S + 1_{\{t \in \text{COVID}\}} x_{i,t}\beta_1^S + \xi_{i,t}. \tag{18}$$

where $\bar{y}_{i,t} - y_{i,t}$ is the difference between nighttime light-adjusted and official GDP growth at the quarterly frequency; $x_{i,t}$ is a row vector of covariates; $1_{\{t \in \text{COVID}\}}$ is a time indicator function that equals 1 during COVID-19 starting in 2020Q1 and 0 otherwise; and $\xi_{i,t}$ is the residual. The interaction term, $1_{\{t \in \text{COVID}\}} x_{i,t}\beta_1^S$, in equation (18) captures the difference between two measures of GDP growth during COVID-19. β_0^S and β_1^S are column vectors of coefficients.

Table 8 presents the results. In addition to the variables in the table, we also control for GDP per capita and the share of GDP generated by agriculture, industry, and services, although none of these variables is statistically significant at least at the 10 percent level.

Column (1) in table 8 shows that higher statistical capacity and higher voice and accountability result in smaller measurement errors. Some examples can again help to strengthen the intuition. The results predict that Kenya has a 0.29 percentage points larger absolute average deviation than Tunisia (0.07 from lower voice and accountability and 0.22 from lower statistical capacity). And indeed, the actual average absolute difference between official and nighttime light-adjusted GDP growth is 0.20 percentage point larger in Kenya than in Tunisia. Similarly, the regression predicts a 0.33 percentage point larger average absolute deviation in Colombia than in Chile (0.17 from voice and accountability and 0.16 from statistical capacity). The actual absolute average deviation between official and nighttime light-adjusted GDP growth is indeed larger in Colombia than in Chile, but at 0.62 percentage point the difference between the two countries is even larger then the regression suggests.

Column (2) allows a different impact in normal times and during the COVID-19 pandemic. It confirms that the results from column (1) hold in normal times and that voice and accountability had an additional, large impact during the pandemic. The results in column (2) also show that countries with larger industrial and service sectors exhibited larger differences between official and nighttime light-adjusted GDP growth during the pandemic.

We next analyze periods of under- and overestimation separately. While statistical capacity reduces both, voice and accountability only reduces overestimation. The nighttime light-adjusted measure suggests a smaller decline in economic activity than reported in the national accounts for countries with a higher share of value added by industry and especially services (and a lower share of value added by agriculture). COVID-19 hit economies with a large service sector especially hard, because the sector relies heavily on human-to-human contact and it was partially shut down to prevent the transmission of the virus. Table I.1 in the appendix shows that both reported as well as nighttime light-adjusted GDP growth during the pandemic declined more with higher shares of services. However, the deviations between the two measures suggest that these countries may have overestimated the impact of COVID-19 (and hence underestimated GDP growth more).

It might seem that the result could reflect a different elasticity of value added in manufacturing and services compared with agriculture. However, we showed in table 5 that the elasticity between countries with above and below median agriculture is nearly the same. Moreover, the elasticity was higher for countries with an above-median share of services, suggesting that a possible bias would not weaken but strengthen the finding.[24]

Table 8. Difference between New and Official Growth Measures

	Absolute difference		Underestimation		Overestimation	
	(1)	(2)	(3)	(4)	(5)	(6)
			difference>0		difference<0	
Voice and accountability	-0.18***	-0.11**	-0.083	-0.094	0.30***	0.12*
	(0.053)	(0.043)	(0.079)	(0.083)	(0.11)	(0.061)
Statistical capacity	-0.014***	-0.017***	-0.017***	-0.018***	0.0099*	0.015***
	(0.0034)	(0.0030)	(0.0037)	(0.0040)	(0.0049)	(0.0044)
Voice and accountability × COVID		-0.56***		-0.11		0.96***
		(0.13)		(0.29)		(0.31)
Statistical capacity × COVID		0.016		0.013		-0.032
		(0.016)		(0.012)		(0.020)
Agriculture share × COVID		0.020		-0.0054		-0.0053
		(0.014)		(0.035)		(0.029)
Industry share × COVID		0.032***		0.067**		0.010
		(0.012)		(0.029)		(0.011)
Service share × COVID		0.074***		0.12**		0.015
		(0.024)		(0.046)		(0.017)
Constant	2.11***	2.01***	2.73**	2.76**	-1.60*	-1.94**
	(0.61)	(0.53)	(1.22)	(1.14)	(0.85)	(0.75)
Date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1965	1965	887	887	1078	1078
Adjusted R^2	0.11	0.12	0.100	0.11	0.14	0.18
Number of countries	76	76	76	76	76	76

Note. The sample includes 76 EMDEs between 2013Q2 and 2020Q4. COVID is a time dummy that equals 1 between 2020Q1 and 2020Q4 and 0 otherwise. Throughout, standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

VII. Heterogeneous Subnational COVID-19 Impacts

With our estimated elasticity, we can quantify different impacts of COVID-19 at the subnational level. Subnational data on economic activity are not often available for EMDEs,

[24]To make the argument work would require arguing that the elasticity between nighttime lights and value added in industry and services declined much less (or increased much more) than the elasticity between nighttime lights and value added in agriculture. However, we are not aware of any reasons to think that this happened.

especially not at quarterly frequency. Nighttime lights provide an alternative way of measuring spatially disaggregated economic activity (see Section V). Our elasticity estimate from Section V.B allows us to translate changes in nighttime lights into changes in economic activity.

We regress regional changes in nighttime lights at quarterly frequency on population density and a region's average nighttime lights per capita, which is a proxy for its level of development. We estimate the following regression model:

$$z_{k,i,t} = x_{k,i}\beta_0^{sub} + 1_{\{t\in\text{COVID}\}}x_{k,i}\beta_1^{sub} + \alpha_i + \delta_t + \xi_{k,i,t}, \tag{19}$$

where $z_{k,i,t}$ is year-on-year nighttime light growth in region k in country i at time t. $x_{k,i}$ is a row vector of average nighttime lights per capita and population density.[25] $1_{\{t\in\text{COVID}\}}$ is a time dummy indicating the COVID-19 period. α_i are country fixed effects and δ_t are time fixed effects. $\xi_{k,i,t}$ is the residual term. β_0^{sub} and β_1^{sub} are column vectors of coefficients.[26]

Column (1) in table 9 shows that higher average nighttime lights per capita are associated with faster growth of nighttime lights over the estimation period. This suggests that regions within countries diverged and spatial inequality rose. The result strengthens when we control for the COVID-19 period (see column (2)) because more developed regions experienced larger declines in nighttime light intensity during the pandemic. Next, we add population density, which is positively related with the level of development and negatively associated with nighttime light growth during COVID-19.[27] Column (3) shows that more populated regions indeed experienced a much larger decline in nighttime lights with the effect being statistically significant at the 1 percent level. A 10 percent higher population density is associated with 1.2 percent lower nighttime light growth.[28] Using an elasticity of 1.55, this is equivalent to 0.77 percent of GDP. The inclusion of population density makes the negative relationship between the level of development and the impact of the pandemic statistically significant at the 1 percent level. During COVID-19, wealthy regions had more options for remote working and therefore might have weathered the impact of COVID-19 better. Ten percent higher average nighttime lights per capita is associated with 0.77 percentage point lower quarterly growth.

[25] Neither is time-varying as we use the average for nighttime lights per capita and population density in 2015. Both are in logs.

[26] A table of summary statistics is included in appendix J.

[27] See figure K.1 in the appendix.

[28] A 10 percent higher population density is about 0.1 in log difference. Multiplied by -11.9, which is the coefficient of the interaction term between population density and COVID in column (3), this implies -1.19 percent in nighttime light growth.

Comparing a few regions shows that these results are plausible. For example, the regression results predict that Phuket darkened more during COVID-19 than Loei (two regions in Thailand), since the former is more developed (nighttime lights per capita are nearly three times as high) and more densely populated (population density is seven times higher).[29] The regression result predicts a 36 percentage point larger decline in nighttime lights in Phuket compared with Loei (12 percentage points for the level of development and 24 percentage points for population density), and indeed, nighttime lights declined by an additional 32 percentage points in the second quarter of 2020. Similarly, the regression results predict that Greater Poland darkened less during COVID-19 than Lesser Poland. While the former is somewhat more developed (by 15.3 percent based on official estimates of GDP per capita and by 21.6 percent based on nighttime lights per capita), the latter has a much higher population density (46 percent higher). Based on the former, we expect nighttime lights in Greater Poland to decline somewhat more (by 2.5 percentage points). However, based on the latter, we expect them to decline much less (by 7.3 percentage points). The net effect of the predicted 4.8 percentage points lower decline in Greater Poland is close to the actual difference of 3.0 percentage points in the second quarter of 2020.

We conduct two robustness checks to see whether the results hold if we control for the 2017Q1 sensor recalibration (see section IV). First, we include a dummy for the period before the recalibration and column (4) shows that the results remain nearly unchanged. Next, we exclude all observations before the recalibration and even then, the changes are minimal and all conclusions hold. We also checked whether controlling for emissions per capita changes the findings, but they are not statistically significant even at the 10 percent level and have no impact on the other results.

VIII. Conclusion

Annual DMSP nighttime light data have already contributed greatly to deepening our economic understanding. With the availability of monthly VIIRS data at an even finer spatial grid and with greatly improved measurement of low-light areas, nighttime lights are becoming an even more important source of information.

In this paper, we initially provided some stylized facts about global VIIRS nighttime light data at quarterly frequency. We documented the need to consider a few technical details

[29] According to official statistics, GDP per capita in Phuket is 3.6 times as large as in Loei, very much in line with the 2.8 times higher nighttime lights per capita.

Table 9. Differentiated Impact of COVID-19 at the Subnational Level

	Nighttime light growth				
	(1)	(2)	(3)	(4)	(5)
Avg. nighttime light per capita	0.47*	0.78*	0.20	0.31	-0.40
	(0.27)	(0.40)	(0.32)	(0.33)	(0.57)
Avg. nighttime light per capita $\times$ COVID		-1.71	-11.7***	-12.2***	-11.9***
		(1.61)	(1.36)	(1.45)	(1.57)
Population density			0.31	0.35	0.15
			(0.21)	(0.22)	(0.34)
Population density $\times$ COVID			-11.9***	-12.2***	-12.1***
			(0.83)	(0.89)	(0.98)
Constant	8.77***	8.84***	0.63	0.70	-4.78***
	(0.88)	(0.89)	(0.91)	(0.90)	(1.12)
Country fixed effects	Yes	Yes	Yes	-	Yes
Date fixed effects	Yes	Yes	Yes	Yes	Yes
2017Q1 adjustment	-	-	-	Yes	-
Starting period	full sample	full sample	full sample	Full sample	$\geq$ 2017Q1
Obs	39176	39176	39176	39176	23301
Adjusted R^2	0.27	0.27	0.32	0.33	0.41

Note. The sample includes 2165 first administrative regions of 116 EMDEs between 2020Q1 and 2020Q4. Nighttime light growth is in percent. Both average nighttime light per capita and population density are in logs. Throughout, country and date fixed effects are included. Standard errors are clustered at the country level and in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

when aggregating the data at the country level, including its geographic coverage, the extent of low-lit areas, and sensor recalibrations. Temporal variations unrelated to economic activity give rise to large noise in nighttime light data, but year fixed effects in regression analyses can control for such noise if it is common across countries. We found that the quarterly correlation between VIIRS nighttime light growth and GDP growth is stronger for EMDEs than for advanced economies.

Different from annual DMSP nighttime light data, monthly VIIRS nighttime light data can be used to study economic short-term impacts of different shocks. To translate changes in nighttime lights measured in nanowatts into changes in economic activity measured in US dollars (or any other currency), elasticity estimates are essential.

In this paper, we presented a novel framework to estimate the elasticity between nighttime lights and GDP. Our framework uses varying degrees of measurement errors in nighttime light data across countries to identify the elasticity. We estimate it to be 1.55 for EMDEs, ranging from from 1.36 to 1.81 across country groups and robust to different model specifications. This elasticity can now be used to translate changes in nighttime lights into changes in economic activity. For example, if the economic impact of a shock is studied with a difference-in-differences approach, a 10 percent decline of nighttime lights in the treated group with respect to the control group reflects an economic impact of 6.5 percent of GDP.[30]

We concluded the paper with two applications. First, we constructed a nighttime light-adjusted measure of GDP growth and showed that more developed countries and those with higher statistical capacity tend to have smaller measurement errors in their national accounts. Widespread efforts to strengthen statistical offices and systems in EMDEs are hence indeed likely to contribute to better economic measurement. However, we also found that low voice and accountability results in higher overestimation of GDP growth, highlighting a crucial role for public scrutiny in ensuring proper measurement. A proper debate about GDP growth in academia, think tanks, and the media is hence important for credible GDP data. Second, we assessed the economic impact of the COVID-19 pandemic and showed that regions with higher levels of development and population density experienced larger declines in economic activity.

[30]To translate changes in nighttime lights to changes in GDP the inverse elasticity, that is $1/\beta$, needs to be used.

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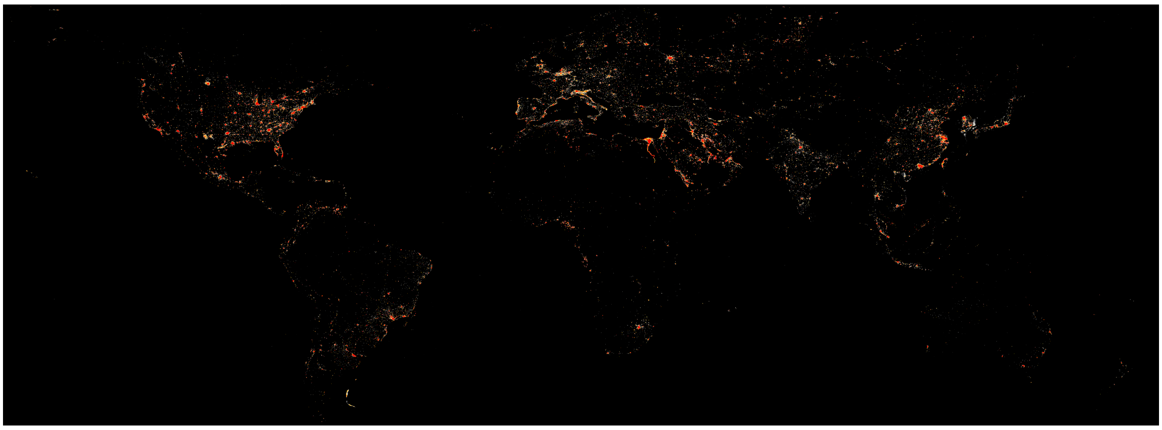
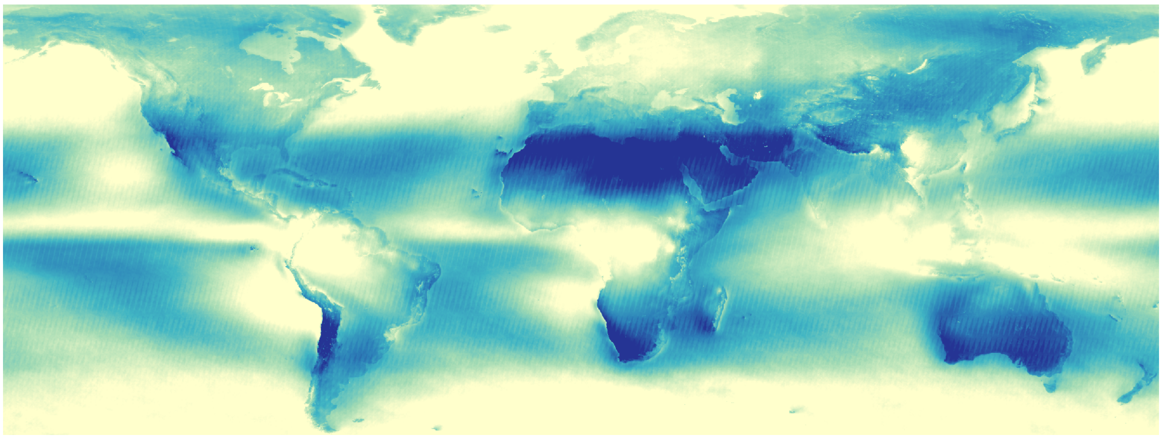
Appendices

Appendix A. More Details on VIIRS Nighttime Light Data

Figure A.1. VIIRS Nighttime Lights and Average Number of Observations



(a) Average nighttime lights



(b) Average number of observations

Note. Panel (a) is the pixel-level average of monthly nighttime lights between April 2012 and December 2020. Darker red indicates more lights at nighttime and black areas indicate no lights. Panel (b) is the pixel-level average number of observations each month. Darker blue indicates a higher number of observations.

Throughout the paper, we use the vcm configuration of VIIRS nighttime lights, which starts from April 2012. VIIRS nighttime lights have two layers. The first layer is average radiance (avg_rad), which is a physical quantity that captures the brightness of lights. The second layer, named cloud-free coverages (cf_cvg), stores the total number of observations that went into each pixel.

Panel (a) in figure A.1 presents the average radiance of VIIRS monthly nighttime lights between April 2012 and December 2020 at the pixel level. The north-south divide is clear. For example, the United States and Europe are much brighter than Latin America and Africa at night.

Panel (b) shows the average number of observations each month at the pixel level, with darker blue indicating more observations. Canada and Europe have fewer observations due to their high latitudes. Tropical areas, particularly the Gulf of Guinea, also have fewer observations owing to higher cloud cover. In contrast, subtropical highs, including the Sahara Desert and most of Australia, have the most observations as a result of dry weather, although those regions are not densely populated.

APPENDIX B. ZERO THRESHOLD AND SENSOR RECALIBRATION

Nighttime light values in low-lit areas affect the sum of nighttime lights at the country level. Due to background noise in the monthly data, low-lit areas may have negative nighttime light values at the pixel level. This happens if low-lit areas are darker than the subtracted background light. Summing the light values of all pixels may even result in negative nighttime lights for small countries in certain months. For example, Panel (a) in figure B.1 shows that the sum of nighttime lights in Sierra Leone is negative in some months before 2017. Applying a threshold of zero reduces the volatility of the sum of nighttime lights and ensures that the sum is always positive.

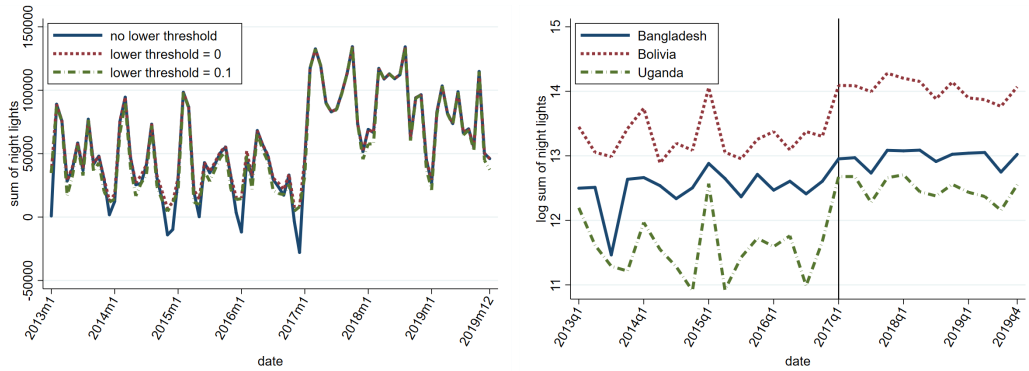
VIIRS underwent a calibration at 14:18 Coordinated Universal Time on January 12, 2017. Panel (b) in figure B.1 shows that the sum of nighttime lights in different parts of the world all experienced some increase, although to varying degrees.

APPENDIX C. COMPARING MONTHLY WITH ANNUAL NIGHTTIME LIGHTS

While our analysis uses quarterly nighttime lights, based on monthly VIIRS data, the Earth Observation Group provides separate annual VIIRS data (VNL-V2) that have undergone an additional filtering and outlier removal process.[31] To examine the difference between monthly and annual data, we compare the annual average of monthly data with VNL-V2 for 185 countries between 2013 and 2019.

[31] See Elvidge and others (2017) for details on the additional cleaning.

Figure B.1. Sum of VIIRS Nighttime Lights at the Country Level



(a) Sierra Leone: Sum of nighttime lights

(b) Log sum of nighttime lights (threshold $= 0$)

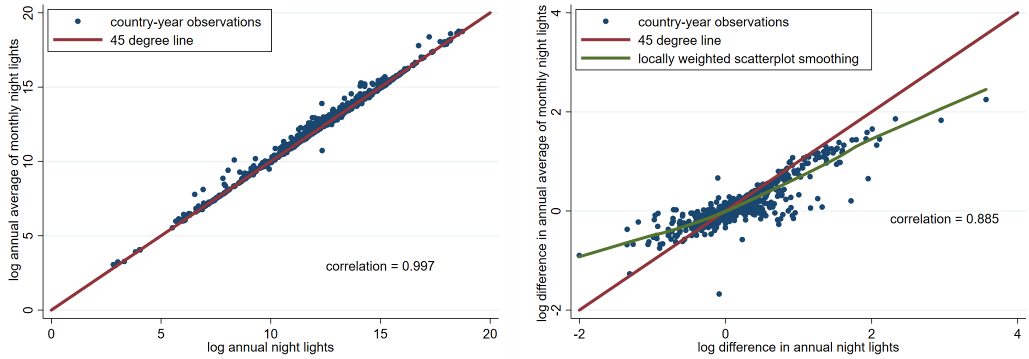
Note. Panel (a) shows the sum of nighttime lights for Sierra Leone with different lower thresholds. Panel (b) shows the log sum of nighttime lights with threshold zero for countries in different continents: Bangladesh (Asia), Bolivia (South America), and Uganda (Africa).

Panel (a) in figure C.1 shows that the sums of nighttime lights averaged across the monthly VIIRS data are strongly correlated with that from the annual VIIRS data, with a very high correlation of 0.997. Panel (b) in figure C.1 shows that the implied annual growth rates of average monthly data are different from those in VNL-V2. In particular, VNL-V2 on average exhibits larger variations, likely because less background noise in annual data makes the change in nighttime lights starker and sharper. Taken together, while the additional filtering and outlier removal process in the annual data have limited impact on the sum of nighttime lights at the country level, the implied growth rates can be quite different, suggesting that elasticity estimates between nighttime lights and GDP from annual and monthly data may not be used interchangeably.

Appendix D. Country Characteristics and Variance of Light Growth

In Section V.B, we use three country characteristics related to the variance of measurement errors in nighttime light growth to identify the elasticity between nighttime lights and GDP: the inverse of the number of valid observations each quarter, the area of each country, and the annual average cloud cover. Since the variance of measurement errors in nighttime light growth is not observable, figure D.1 examines the relationships between the variance of nighttime light growth and those country characteristics. The correlation with the number of valid observations in Panel (a) and that with cloud cover in Panel (c) are similar, which is intuitive as more cloud cover implies less number of valid observations. The correlation with country area in Panel (b) is much weaker. While cloud cover is

Figure C.1. VIIRS Nighttime Lights, 2013-2019: Monthly versus Annual

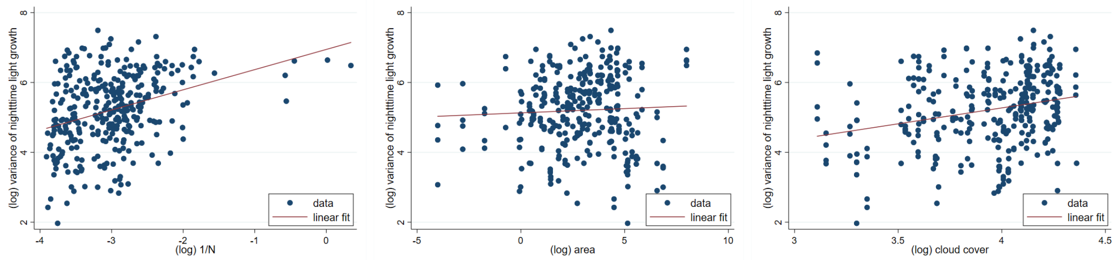


(a) Level **(b) Growth rate**

Note. This graph compares annual average of monthly nighttime lights (vcm version) at the country level against annual nighttime lights (VNL V2). Throughout, we apply a lower threshold of zero. To calculate the average of monthly nighttime lights for each country, we use only months for which there are complete observations of the country, that is, no nighttime lights at the second administrative level regions are missing.

fixed over time, the number of valid observations is time-varying and hence exhibits more variation. We use the inverse of the number of valid observations as the control variable in our baseline.

Figure D.1. Country Characteristics and Variance of Nighttime Light Growth



(a) Number of observations **(b) Area** **(c) Cloud cover**

Note. This panel of scatter plots presents the relationships between the variance of nighttime light growth and country characteristics that are used to identify the elasticity between nighttime lights and GDP. The country characteristics include the inverse of the number of daily nighttime light observations in each quarter, the area of a country, and the average cloud cover of a country. Each dot represents a country-period observation, where each period is two years that are used to calculate the variance of nighttime light growth. While the number of observations for a country is time-varying, area and cloud cover are fixed.

Appendix E. Data Winsorization

Section V.C conducts robustness checks of the elasticity estimate in regression (8) with various winsorization of nighttime lights and GDP data. Table E.1 presents a subset of estimates in Figure 2. The upper panel considers winsorization by GDP growth, with the top and bottom 5 percent of the nighttime light growth distribution excluded throughout. The lower panel considers winsorization by nighttime light growth, with the top and bottom 1 percent of the GDP growth distribution excluded throughout. Overall, the elasticity estimate, which is the coefficient before the covariance term, is more sensitive to the extreme ends of the distribution of nighttime light growth than it is to that of GDP growth. In our baseline estimation, we remove the top and bottom 5 percent of the nighttime light growth distribution as well as the top and bottom 1 percent of the GDP growth distribution.

Table E.1. Elasticities between Night Lights and GDP: Various Winsorization

Winsorization by GDP growth

	Variance of night light growth: var(z)			
	(1)	(2)	(3)	(4)
Threshold	0.5%	1%	2%	5%
cov(y, z)	1.89***	1.55***	1.85***	1.69**
	(0.56)	(0.54)	(0.57)	(0.69)
$1/N$	525.9***	522.0***	499.6***	560.4***
	(141.1)	(139.8)	(143.9)	(146.5)
Obs	327	327	325	320
Adjusted R^2	0.063	0.056	0.057	0.053

Winsorization by nighttime light growth

	Variance of night light growth: var(z)			
	(1)	(2)	(3)	(4)
Threshold	1%	2%	5%	10%
cov(y, z)	2.38**	3.07***	1.55***	1.29***
	(1.21)	(1.02)	(0.54)	(0.38)
$1/N$	586.0***	562.4***	522.0***	205.7*
	(164.5)	(171.2)	(139.8)	(109.6)
Obs	327	327	327	321
Adjusted R^2	0.044	0.050	0.056	0.038

Note. This table presents the results of regression (8) with various winsorization of nighttime lights and GDP data. In the upper panel, the sample removes the extreme ends of the GDP growth distribution with increasingly higher thresholds from column (1) to column (4), with the top and bottom 5 percent of the nighttime light growth distribution excluded throughout. In the lower panel, the sample removes the extreme ends of night light growth distribution with increasingly higher thresholds from column (1) to column (4), with the top and bottom 1 percent of the GDP growth distribution excluded throughout. In each panel, the first row represents estimates of the elasticity between nighttime lights and GDP. Each time period used to estimate the variances and covariances covers two years, that is, 2013-14, 2015-16, 2017-18, and 2019-20. Throughout, standard errors are in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

APPENDIX F. ALTERNATIVE ELASTICITY ESTIMATION

In equation (8), we observe that for each country i, there is a trade-off between the number of observations used to estimate var$(z_{i,t})$ and cov$(y_{i,t}, z_{i,t})$ and the number of variances and covariances to estimate β. Since we have almost eight years of quarterly data, if we use two years of data to calculate the variances and covariances, which is what we do in section V.B, we are left with four observations from each country to estimate β.

Alternatively, one can use more observations to obtain more accurate variances and covariances, but ends up with fewer observations to estimate β. Table F.1 presents results when we use three and four years of data to estimate the variances and covariances, respectively. The point estimates are very similar to those in table 4, which is reassuring as they are robust to alternative groupings. However, the statistical significance of the coefficients declines, indicating that the point estimates become imprecise when the number of observations is reduced.

Table F.1. Elasticities between Nighttime Lights and GDP

Grouping by three years					
	Variance of night light growth: var(z)				
	(1)	(2)	(3)	(4)	(5)
cov(y,z)	1.01	1.38**	1.18*	1.40*	1.56**
	(0.72)	(0.70)	(0.71)	(0.73)	(0.71)
$1/N$		746.3***			754.7***
		(150.3)			(247.2)
Area			0.14***		-0.039
			(0.045)		(0.070)
Cloud cover				3.82***	2.22*
				(1.18)	(1.22)
Obs	246	246	246	240	240
Adjusted R^2	0.0038	0.092	0.038	0.041	0.099

Grouping by four years					
	Variance of night light growth: var(z)				
	(1)	(2)	(3)	(4)	(5)
cov(y,z)	0.96	1.04	1.03	1.18	1.08
	(0.95)	(0.91)	(0.94)	(0.95)	(0.92)
$1/N$		662.4***			872.2***
		(162.5)			(285.3)
Area			0.10**		-0.11
			(0.049)		(0.080)
Cloud cover				3.56***	1.82
				(1.25)	(1.31)
Obs	166	166	166	162	162
Adjusted R^2	0.00013	0.087	0.021	0.042	0.10

Notes. This table presents the results of regression (8) and its variant with other covariates. The sample includes 84 EMDEs between 2013Q2 and 2020Q4. In the top panel, each time period used to estimate the variances and covariances covers three years, that is, 2013-15, 2016-2018, and 2019-20. In the bottom panel, each time period used to estimate the variances and covariances covers four years, that is, 2013-16 and 2017-20. In each panel, the first row represents estimates of the elasticity between nighttime lights and GDP. Throughout, standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

APPENDIX G. LIGHT-PREDICTED GDP

The optimal weight calculation requires the estimation of γ in equation (9). Table G.1 presents the estimation result. We use the coefficient before nighttime light growth in column (4).

Table G.1. VIIRS Nighttime Lights: Predicting GDP Growth for EMDE

	GDP growth (yoy)			
	(1)	(2)	(3)	(4)
Nighttime light growth (yoy)	0.0123*	0.0110	0.0225***	0.0157***
	(0.00717)	(0.00646)	(0.00599)	(0.00392)
Country fixed effects	-	Yes	-	Yes
Date fixed effects	-	-	Yes	Yes
Obs	2158	2158	2158	2158
Adjusted R^2	0.00272	0.203	0.377	0.586

Note. This table presents the regression results of GDP growth on nighttime light growth for EMDEs, incrementally controlling for time and country fixed effects. Throughout, standard errors are clustered by time and in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Appendix H. Summary Statistics for Regressions (17) and (18)

Table H.1 presents the distributional statistics of control variables used in equations (17) and (18).

Table H.1. Summary Statistics of Control Variables, Average 2013-2020

	Mean	p10	p25	p50	p75	p90
Statistical capacity	74.5	55.8	68.1	76.4	83.8	88.5
Voice and accountability	-0.2	-1.1	-0.6	-0.1	0.3	0.6
GDP per capita	12.4	2.2	5.3	11.9	17.5	25.8
Agriculture share	11.7	3.4	5.0	8.3	15.8	25.9
Industry share	26.6	16.1	21.6	25.5	30.7	36.2
Service share	52.9	41.1	47.4	54.1	58.9	61.9

Note. GDP per capita is in thousands of constant 2017 international dollar in purchasing power parity terms. p10, p25, p50, p75, and p90 indicate the 10th, 25th, 50th, 75th, and 90th percentile, respectively.

Appendix I. COVID-19 Impact: Official and New GDP Growth

Table I.1 examines economic performance during the pandemic as measured by official GDP growth and nighttime light-adjusted GDP growth.

Table I.1. COVID-19 Impact: Official and New GDP Growth Measures

	(1)	(2)	(3)	(4)
	Official		Light-adjusted	
Voice and accountability	-0.14	0.11	-0.13**	-0.063
	(0.17)	(0.092)	(0.055)	(0.041)
Statistical capacity	0.039***	0.039***	0.038***	0.038***
	(0.0073)	(0.0078)	(0.0037)	(0.0042)
Voice and accountability $\times$ COVID		-1.78**		-0.45**
		(0.66)		(0.20)
Statistical capacity $\times$ COVID		-0.017		-0.0093*
		(0.015)		(0.0050)
Agriculture share $\times$ COVID		0.035		0.049
		(0.10)		(0.053)
Industry share $\times$ COVID		-0.054		0.011
		(0.036)		(0.019)
Service share $\times$ COVID		-0.15***		-0.023
		(0.040)		(0.021)
Constant	-5.21**	-4.45**	-4.24***	-4.08***
	(2.03)	(1.82)	(0.96)	(0.91)
Date fixed effects	Yes	Yes	Yes	Yes
Obs	1949	1949	1949	1949
Adjusted R^2	0.45	0.47	0.71	0.71

Note. The sample includes 76 EMDEs between 2013Q2 and 2020Q4. COVID is a time dummy that equals 1 between 2020Q1 and 2020Q4 and 0 otherwise. Throughout, standard errors are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

APPENDIX J. SUMMARY STATISTICS FOR REGRESSION (19)

Table J.1 presents the distributional properties of the first administrative (admin-1) regions and summary statistics of variables at the subnational level used in equation (19). Both average nighttime lights per capita and population density are highly skewed at the admin-1 level, as can be seen in the large difference between their respective mean and median. This indicates that the use of their logarithms is more appropriate, which we do in regression (19).

Table J.1. Summary Statistics of Variables at the Subnational Level

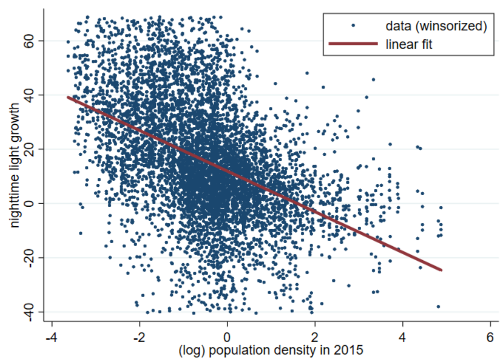
	mean	p10	p25	p50	p75	p90
Property of admin-1 regions						
Number of regions per country	19	5	9	14	24	34
Area of regions (1000km^2)	43.5	1.7	3.6	9.8	35.7	101.7
Control variables for admin-1 regions (winsorized)						
Average nighttime lights per capita	0.053	0.012	0.022	0.041	0.069	0.11
(log) average nighttime lights per capita	-3.24	-4.45	-3.82	-3.20	-2.67	-2.18
Population density (100 per km^2)	2.03	0.13	0.33	0.69	1.40	3.55
(log) population density	-0.37	-2.07	-1.12	-0.37	0.34	1.27

Note This table presents summary statistics of subnational variables used in Table 9 of Section VII. The control variables are winsorized at the extreme ends as in table 9. p10, p25, p50, p75, and p90 indicate the 10th, 25th, 50th, 75th, and 90th percentile, respectively.

APPENDIX K. POPULATION DENSITY AND COVID-19 IMPACT

Figure K.1 presents the scatter plot of nighttime light growth and population density at the subnational level, which shows a strong negative correlation.

Figure K.1. Nighttime Light Growth during COVID-19 and Population Density



Note. This graph contrasts nighttime light growth in each quarter of 2020 against population density in 2015 at the subnational level. Each dot represents a region-quarter observation, where the region is the first administrative region of a country.