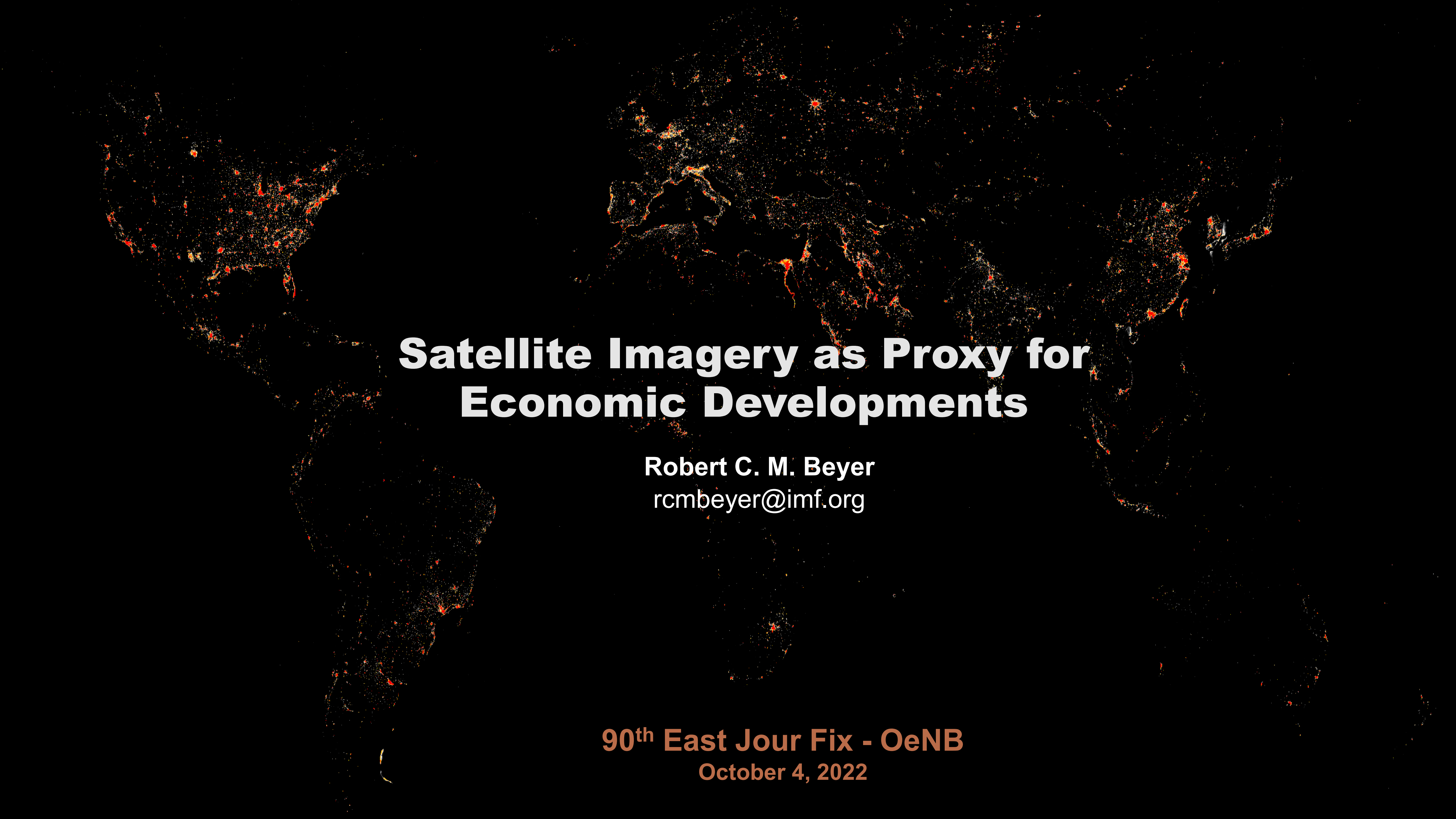

Satellite Imagery as Proxy for Economic Developments

Robert C. M. Beyer
rcmbeyer@imf.org

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Data from satellite imagery can contain economic information

1) Remote sensing data usually have four advantages:
   - access to information difficult to obtain by other means
   - unusually high spatial resolution
   - wide geographic coverage
   - mostly low costs (especially compared to survey data)

2) Technology start-ups use such data to track industrial storage facilities (e.g., open oil tanks), factory and retail parking lots, port utilization, *etc.*

3) Economists use such data to obtain information on nighttime light, precipitation, flooding, topography, forest cover, crop choice, agricultural productivity, urban development, building type, roads, beach quality, air pollution (particulate matter), CO_2, *etc.*

$\Rightarrow$ Donaldson and Storeygard (2016) provide a great summary of applications in economics.

Overview of nighttime light data

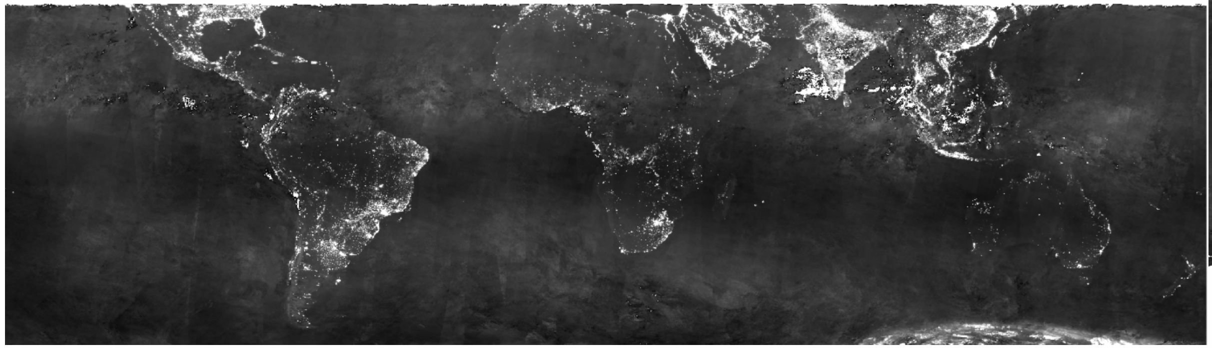
- **Annual DMSP-OLS (1992-2013)**
  - Widely used to for geographical mapping of economic activity, subnational development analysis, and the evaluation of the national accounts (Henderson, Storeygard, and Weil 2012; Keola, Andersson, and Hall 2015; Pinkovskiy and Sala-i-Martin 2016; Henderson, Squires, Storeygard, and Weil 2018; Morris and Zhang 2019, Gibson, Olivia, and Boe-Gibson 2020, Hu and Yao 2021; *etc.*)

- **Monthly VIIRS (2012 April – present)**
  - Relatively understudied
  - Available for free with short publication lag from the *Earth Observation Group*
  - Higher granularity and frequency offer new opportunities, for example to analyze
    - India's demonetization (Beyer, Chhabra, Galdo, and Rama 2018; Chodorow-Reich, Gopinath, Mishra, and Narayanan 2020)
    - the impact of the US-China trade war (Chor and Li 2021)
    - the impact of COVID-19 (Elvidge, Ghosh, Hsu, Zhizhin, Bazilian 2020 for China; Beyer, Galdo, Franco-Bedoya 2021 for India)

Two important caveats of VIIRS data

1) **The data is very noisy**
   - Fires, gas flaring, moon cycle, ships, *etc.*
   - The data needs to be cleaned to strengthen the relationship with economic activity => from lights to man-made lights

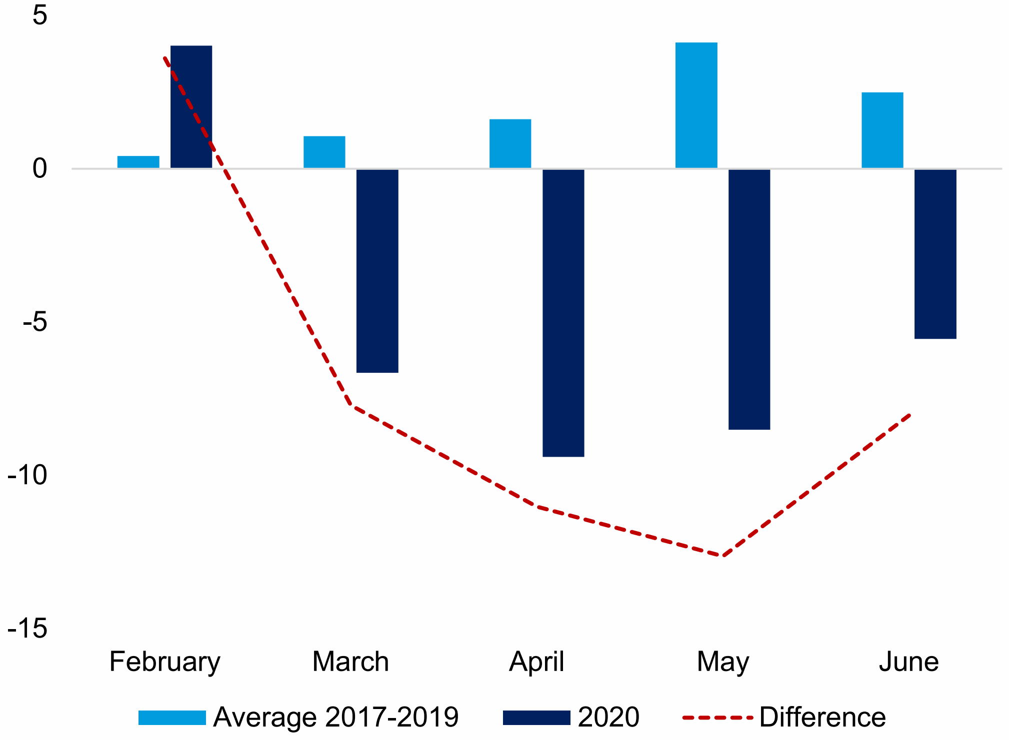
2) **The data is incomplete toward the North and South poles**
   - The monthly coverage depends on the month and the region

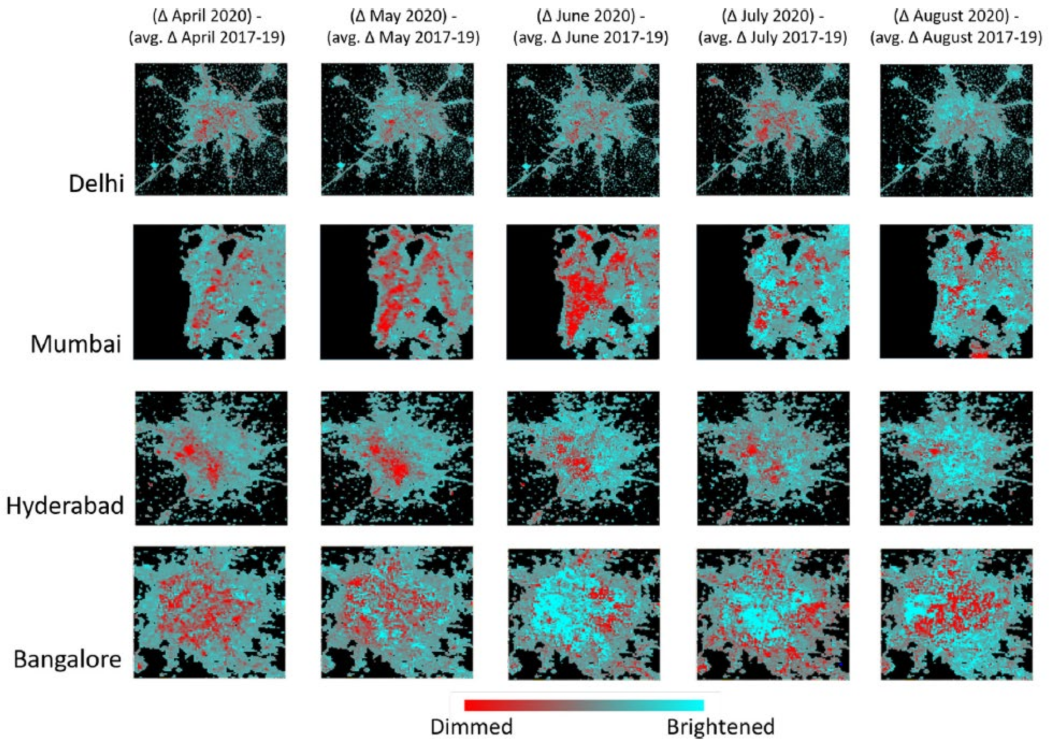


June 2020

December 2020

Nighttime light can provide economic insights, for example on the disruption from COVID-19 in India

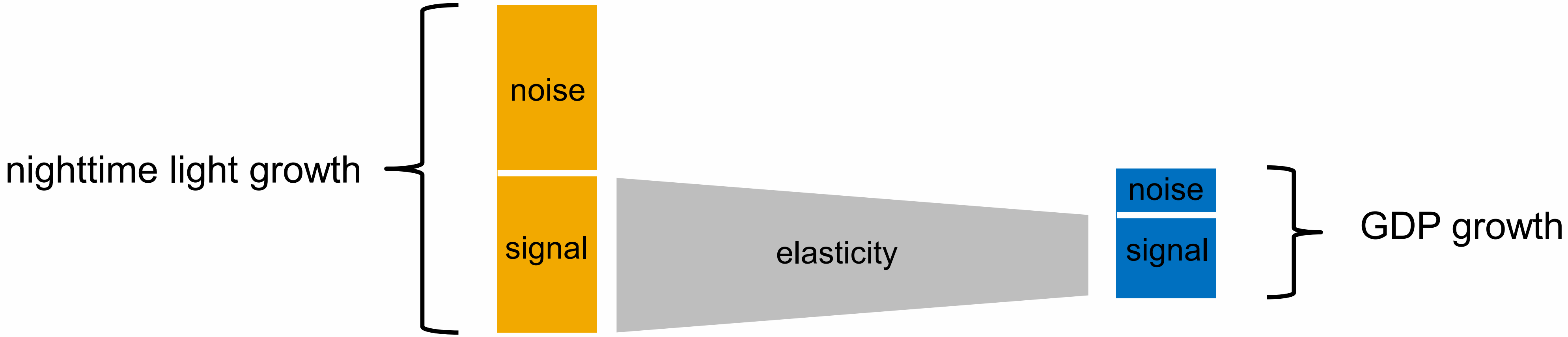




- ➢ Important finding: despite the national restrictions, districts with higher infection rates experienced larger declines in nighttime lights.

Source: Beyer, R. C., Franco-Bedoya, S., & Galdo, V. (2021). Examining the economic impact of COVID-19 in India through daily electricity consumption and nighttime light intensity. *World Development*, *140*, 105287.

Nighttime light and GDP are correlated, but both are noisy measures of economic activity.



The problem: if GDP growth changes by *x*%, how much change in nighttime light does that imply?

Nighttime light growth: $z_t = \boldsymbol{\beta} y_t^* + \epsilon_t^z$

GDP growth: $y_t = y_t^* + \epsilon_t^y$

Translating changes in light into changes in GDP

- **Variance-covariance equations (3 equations, 4 unknowns)**

$$\boldsymbol{var(y_t)} = var(y_t^*) + var(\epsilon_t^y)$$

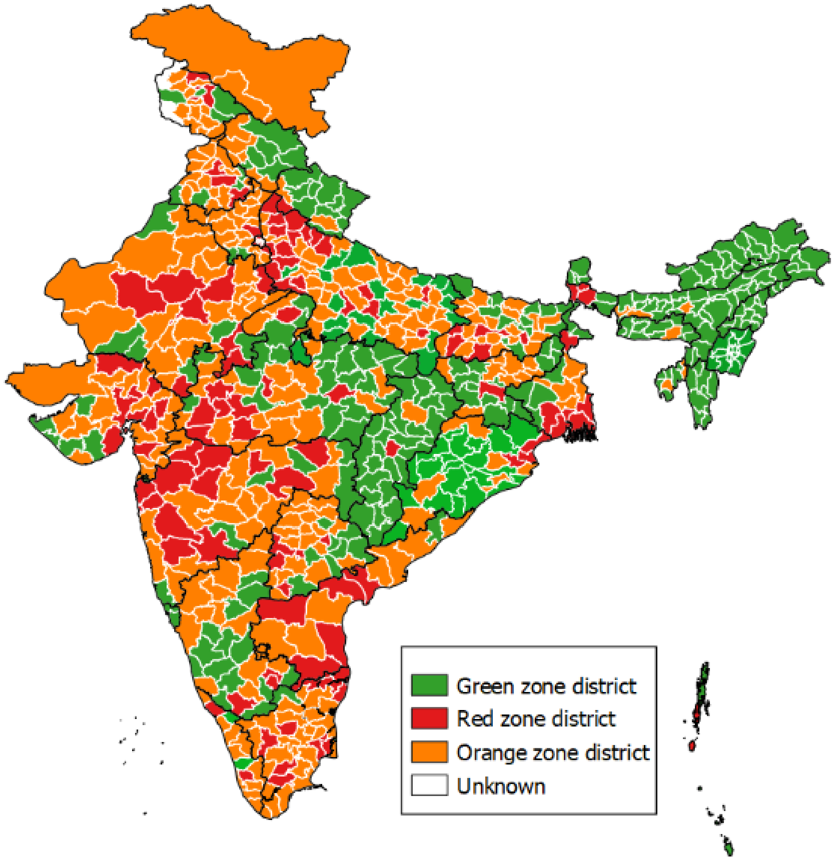
$$\boldsymbol{var(z_t)} = \beta^2 var(y_t^*) + var(\epsilon_t^z)$$

$$\boldsymbol{cov(y_t, z_t)} = \beta var(y_t^*)$$

- **We need one piece of auxiliary information**
  - Henderson, Storeygard, and Weil (2012): $var(\epsilon_t^y) = 0$ for Advanced Economies
  - Hu and Yao (2021): ϵ_t^y depends on statistical capacity and ϵ_t^z on location (cloud cover)
  - Beyer, Hu, Yao (2022): $var(\epsilon_t^z)$ is proportional to the number of effective daily observations, which results in the following regression equation $var(z) = \boldsymbol{\beta}\, cov(y, z) + \alpha \frac{1}{N} + \zeta$.
    (see appendix for more details)

Nighttime lights can be used to study the impact of policies, for example of mobility restrictions.

Covid-19 containment measures



Declines in nighttime light intensity

	(1)	(2)	(3)
Red zone district	-1.678***	-0.307***	-0.277***
	(0.064)	(0.042)	(0.039)
Orange zone district	-0.335***	-0.043*	-0.054**
	(0.052)	(0.024)	(0.022)
Controls	No	Yes	Yes
Previous year nightlight	No	No	Yes
State FE	Yes	Yes	Yes
R-squared	0.29	0.81	0.83
Number of observations	3460	3460	3460

Notes: Standard errors are clustered at the state level.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

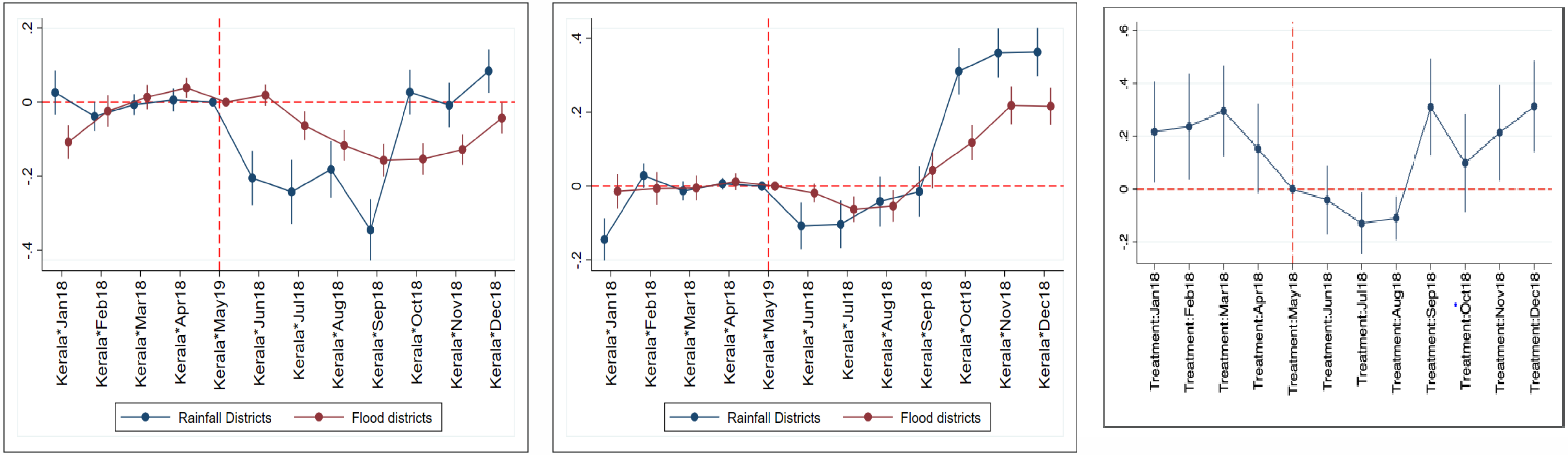
$$y_i^1 - y_i^0 = \beta_0 + \beta_1 Red_i + \beta_2 Orange_i + \beta_3 \mathbf{X}_i + StateFE_i + \epsilon_{it}$$

Source: Beyer, R. C. M., Jain, T., & Sinha, S. (2021). *Lights Out? COVID-19 Containment Policies and Economic Activity (No. 9485). World Bank Policy Research Working Paper, Washington DC.*

Nighttime lights can complement studies of natural disasters, for example floods.

The impact of the Kerala Floods in 2018 relative to unaffected districts

Household expenditure | Household income | Nighttime light intensity



Source: Beyer, R. C. M., Narayanan, A., Thakur, G. M. 2022. Natural Disasters and Economic Dynamics: Evidence from the Kerala Floods (No. 10084). *World Bank Policy Research Working Papers*, Washington, DC.

But can nighttime light data improve our GDP forecasts?

- So far, nighttime lights have been found to improve now- and forecasts statistically, but not economically meaningful
  - Galimberti (2020) shows that DMSP-OLS nighttime lights can improve annual forecasts relative to an AR(1) forecast.
  - Beyer, Bhaduri, and Pahul (2018) show that VIIRS nighttime light data can improve quarterly nowcasts of services in India when there is not a lot of other data yet.

- VIIRS data could potentially be useful in the future
  - A more meaningful spatial aggregation of nighttime light data could potentially dramatically improve its forecasting capabilities (potentially based on machine learning techniques)
  - The sample seems still too short to do proper model estimation and out-of-sample testing
  - It will likely be more useful in countries with little other high-frequency data available with short lags

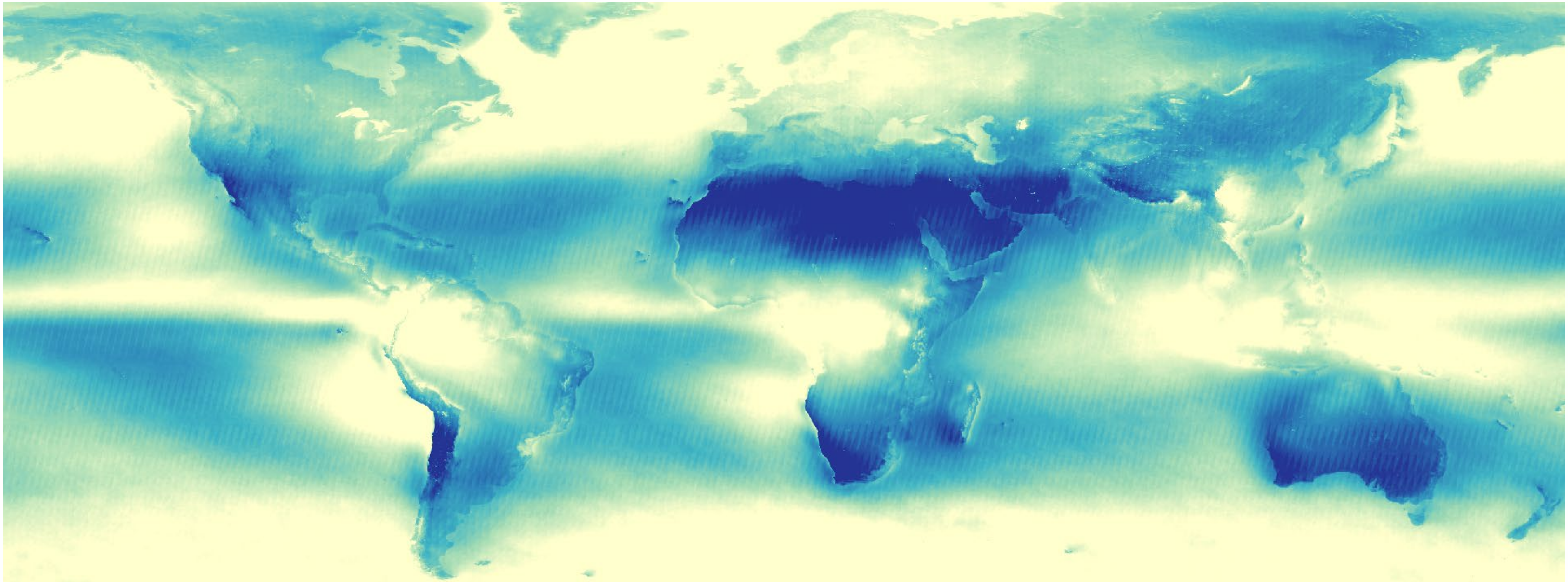
Appendix

Contribution of Beyer, Hu, and Yao (2022)

- The paper puts together a monthly global nighttime light data set
- It estimates a quarterly elasticity between GDP growth and nighttime light growth (ranging from 1.36 to 1.81 across country groups)
- Constructs a light-adjusted measure of quarterly economic activity
- Shows that
  - Higher levels of development, statistical capacity, and voice and accountability are associated with more precise national accounts data
  - Regions with higher levels of development and population density experienced larger declines in economic activity during COVID-19.

Source: Beyer, R. C. M., Hu, Y., & Yao, J. (2022). *Measuring Quarterly Economic Growth from Outer Space* (No. 2022/119). International Monetary Fund Working Paper, Washington DC.

Heterogeneity of number of effective daily VIIRS observations per quarter.



Note: Darker colors imply more observations.
Source: Beyer, R. C. M., Hu, Y., & Yao, J. (2022). *Measuring Quarterly Economic Growth from Outer Space* (No. 2022/119). International Monetary Fund Working Paper, Washington DC.

Estimating the elasticity

$$y_{i,t} = y_{i,t}^* + \epsilon_{i,t}^y$$

$$z_{i,t,j} = \boldsymbol{\beta} y_{i,t}^* + \epsilon_{i,t,j}^z \longrightarrow z_{i,t} = \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} z_{i,t,j} = \boldsymbol{\beta} y_{i,t}^* + \frac{1}{N_{i,t}} \sum_{j=1}^{N_{i,t}} \epsilon_{i,t,j}$$

Taking variances and covariances:

$$var(z_{i,t}) = \beta^2 var(y_{i,t}^*) + \frac{1}{N_{i,t}} \sigma_{\epsilon_z}^2$$

$$cov(y_{i,t}, z_{i,t}) = \beta var(y_{i,t}^*)$$

Substituting:

$$var(z_{i,t}) = \beta cov(y_{i,t}, z_{i,t}) + \frac{1}{N_{i,t}} \sigma_{\epsilon_z}^2$$

Regression equation:

$$var(z) = \boldsymbol{\beta}\, cov(y, z) + \alpha \frac{1}{N} + \zeta$$

Elasticity estimates

$$var(z) = \boldsymbol{\beta}\, cov(y,z) + \alpha \frac{1}{N} + \zeta$$

	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

Heterogeneity across countries

	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