Measuring Inequality using Geospatial Data

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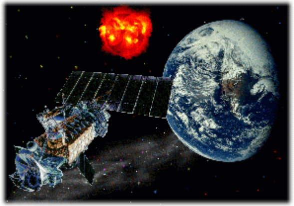
Motivation

- Rising inequality over recent decades with important social and economic consequences (Piketty and Saez, 2014; Lakner and Milanovic, 2016).
- Limited availability of consistent data at a global scale.
  - Quality, sources and methods vary across countries (Atkinson and Brandolini, 2001).
  - Household surveys under-sample richer households (Deaton, 2005).
  - Tax records affected by tax evasion and not available consistently (Galbraith, 2019).
  - Hard to account for informal sector (Alstadsæter et al., 2019).
  - Existing global inequality databases with many missing data points and wide confidence intervals.

◆ We propose a measure based on geospatial data that are internationally comparable and globally available.

The View from Outer Space

- Remote sensing applied to social sciences, e.g.: epidemiology, disaster management, population size and location, economic growth and poverty.
- Satellite-recorded data on nighttime lights emited from Earth and visible from space.



Defense Meteorological Satellite Program

- Night lights data in economics:
  - As a complement to national GDP statistics (Henderson et al., 2012; Nordhaus and Chen, 2015; Pinkovskiy and Sala-i Martin, 2016).
  - Geographic mapping of economic activity (Mellander et al., 2015; Bickenbach et al., 2016; Henderson et al., 2018).
  - Regional development analysis (Michalopoulos and Papaioannou, 2013b,a).
  - Measurement of inequality (Elvidge et al., 2012; Alesina et al., 2016; Lessmann and Seidel, 2017).

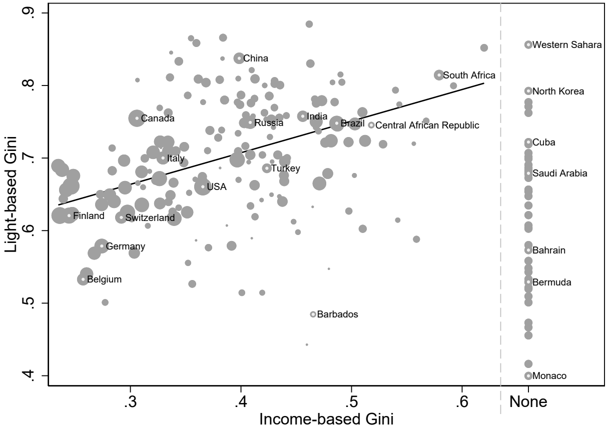
Contribution

- A measure of economic inequality using night lights and gridded population data.
  - Light-based Gini-coefficients for 234 countries/territories from 1992 to 2013.

▸ List of Countries and Territories

- Methodological innovations.
  - Different sources of gridded population data.
  - Varying levels of geographical aggregation.
  - Calibrated to income inequality (SWIID, Solt, 2016).
- Three applications in health economics and international finance for illustrative purposes.

Sneak Peek



- Light Ginis are positively correlated with income Ginis.
- Stronger correlation with higher-quality data (larger bubbles).
- 47 countries/territories without income measure.

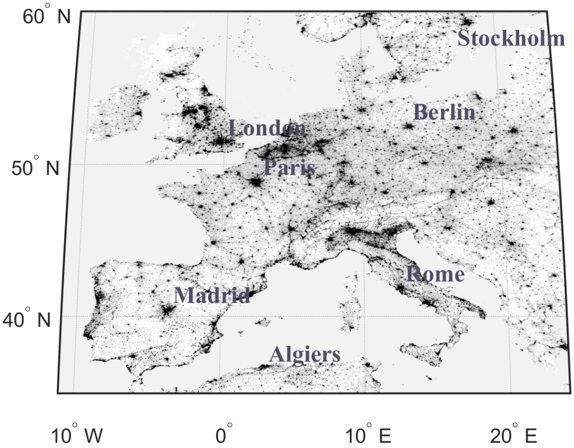
Time Series

Outline

1. Motivation
2. Source Data and Measurement Issues
3. Geospatial Inequality Measures
4. Applications
5. Concluding Remarks

Night Lights Data (DMSP/NOAA)

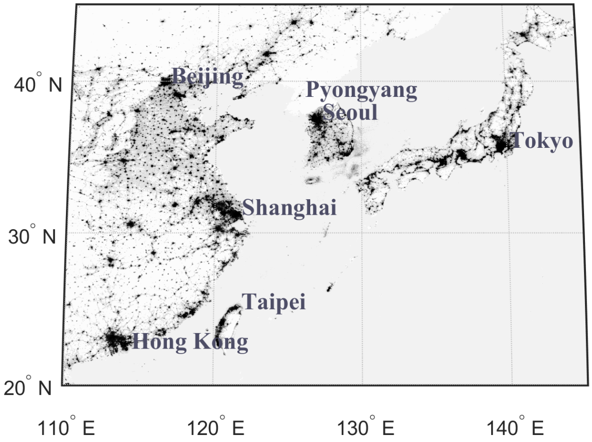
Average Lights over Europe – 2013



- Global grid of 30 arc second cells with 6-bit digital number (DN) values [0-63] of light intensity.
- Annual average of cloud-free observations, also discarding images affected by sun and moonlight, aurora lighting.

Night Lights Data (DMSP/NOAA)

Average Lights over East Asia – 2013



- Measurement issues: sensor saturation/top-coding, low-coding, satellite intercalibration, blurring/blooming, gas flares.

Data Stats

Lights and Economic Activity

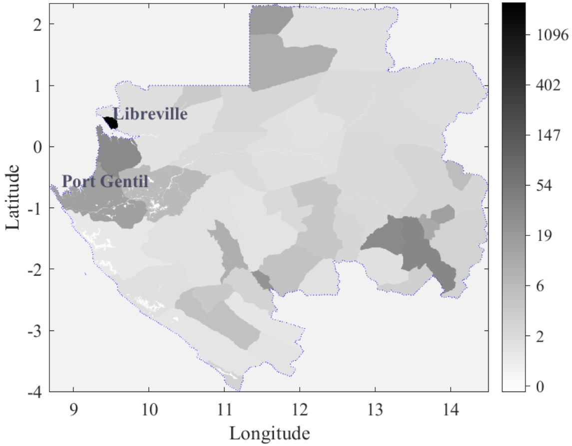
- Relationship between lights and economic activity is not necessarily linear:

$$x_i = DN_i^{\kappa},$$

  where each pixel i's digital number (DN) is coverted to a light-based measure of economic activity, x_i.
- Estimation of κ at pixel level is very difficult:
  - No data on x_i at such disaggregated level.
  - Likely more heterogeneous than panel aggregate estimates (Bickenbach et al., 2016; Hu and Yao, 2019; Galimberti, 2020).
- We follow an agnostic calibration approach and consider:
  - $\kappa = \{0.5, 1.0, 1.5, 2.0, 3.0, 5.0\}$

Gridded Population of the World (GPW/CIESIN)

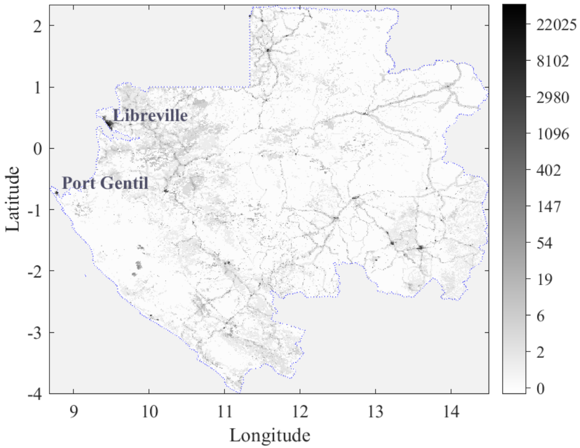
Gabon's Population Counts – 2010



- Population census data collected for administrative census areas and disaggregated to grid cells.
- Extrapolated from censuses occurring between 2005 and 2014.
- Measurement issue: uniform distribution within census areas!

LandScan Global Population (LSC/ORNL)

Gabon's Population Counts – 2010



- Census data disaggregated using: land cover, roads, slope, urban areas, village locations, high-resolution imagery.
- Available from 2000, updated annually.
- Measurement issue: time-inconsistency!

Construction of Geospatial Inequality Measures

- **Goal:** Calculate country-year Gini-coefficients based on gridded geospatial data on night lights and population counts.
- **Stage 1:** calculate 12 geospatial Gini-coefficients.
  - Different levels of aggregation: census-level (GPW), pixel-level (LSC)
  - Different lights scaling parameters: $\kappa = \{0.5, 1.0, 1.5, 2.0, 3.0, 5.0\}$.
- **Stage 2:** generate final light-based Gini-coefficients weighting 12 Ginis above.

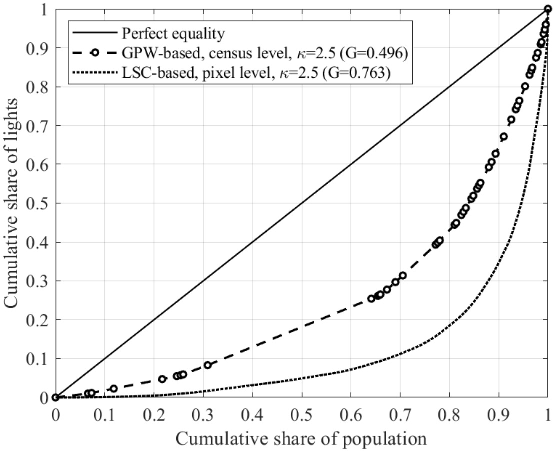
$$G^{w} = \sum_{i=1}^{12} \omega_i G_i^{g}.$$

  - Weights that maximize correlations with SWIID inequality measures:

$$\max_{\{\omega_i\}_{i=1}^{12}} \{\lambda Corr_{cross}(w) + (1-\lambda)\, Corr_{within}(w)\}$$

Stage 1: Geospatial Gini-coefficients

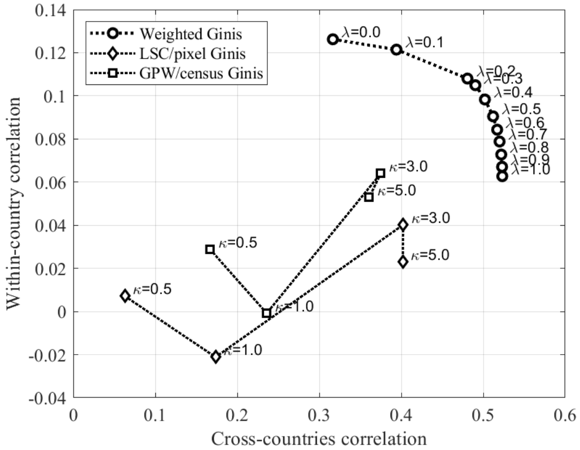
Light-based Inequality in Gabon – 2010



- Rank spatial units by lights per capita.
- Sum up the cumulative shares of lights versus cumulative shares of population in a country – Lorenz curve.
- Gini is the area between line of perfect equality and the Lorenz curve.

Summary Stats

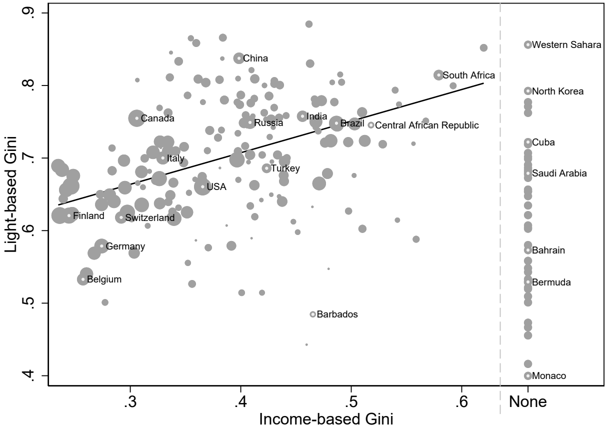
Stage 2: Weighted Light-based Gini-coefficients



- Dot = correlations averaged across all countries and years.
- Dominance of weighted Ginis.
- Trade-off between cross- and within country correlations.
- $\lambda = 0.5$ provides a good compromise.

Correlations | Weights
Summary Stats | Area | Light/Area

Sneak Peek



- Light Ginis are positively correlated with income Ginis.
- Stronger correlation with higher-quality data (larger bubbles).
- 47 countries/territories without income measure.

Time Series

Applications

- Compare how the light- and income-based inequality measures correlate with different (potential) determinants of inequality.
  - Epidemics.
  - Capital account liberalization.
  - (Out-of-pocket health care expenditures)
- Unified empirical approach:

$$G_{c,t} = \gamma z_{c,t} + \delta_t + \alpha_c + \epsilon_{c,t},$$

where

- $G_{c,t}$: light- and income-based Gini-coefficients for country c in year t.
- $z_{c,t}$: variable of interest according to application.
- δ_t and α_c: time and country fixed effects.
- Gini-coefficients are normalized – estimates are std. devs. from sample mean.

Epidemics and Inequality

- Literature:
  - Côte d'Ivoire: AIDS-induced mortality reduces household income, but has no significant effect on income distribution (Cogneau and Grimm, 2008).
  - Malawi: people living in neighborhoods with higher wealth inequality face a higher risk of HIV infection (Durevall and Lindskog, 2012).
  - Sweden: increase in poverty due to 1918 Spanish flu (Karlsson et al., 2014).
- We use data on epidemic disasters from the Centre for Research on the Epidemiology of Disasters (CRED, 2019).
  - Disaster criteria: (i) 10 or more deaths; (ii) 100 or more people affected; (iii) country declares state of emergency or (iv) calls for international assistance.
  - Percentage of individuals within each country that were affected by an epidemic during the year.

Summary Statistics

Epidemics and Inequality

Robustness

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Income-based Gini	6.903**	0.332**		6.246***	0.829*	
	(2.750)	(0.147)		(2.201)	(0.446)	
Light-based Gini	6.710***	-0.328	-1.065	5.749***	-0.264	-0.245
	(1.562)	(0.721)	(0.817)	(1.185)	(0.367)	(0.432)
Observations	3278	3278	5148	3278	3278	5148
# of countries	187	187	234	187	187	234
Country fixed effects	no	yes	yes	no	yes	yes
Population weights	no	no	no	yes	yes	yes

Notes: Each coefficient is a separate regression with % people affected by epidemics as explanatory.

- Lights data are less prone to effects of transitory income shocks, while still capturing long run effects of regular incidence of epidemics.

Capital Account Liberalization and Inequality

- Literature:
  - Liberalization can lead to lower income inequality for countries with high level of financial depth (Bumann and Lensink, 2016).
  - Liberalization tends to increase inequality, depending on quality of political institutions and level of financial development (De Haan and Sturm, 2017).
  - Episodes of capital account liberalization increase income inequality, particularly in countries that lack financial depth (Furceri and Loungani, 2018).
- We use data from the Chinn and Ito (2008) index of financial openness.
  - Based on PCA of IMF data on restrictions to cross-border financial transactions.

Summary Statistics

Capital Account Liberalization and Inequality

▸ Robustness

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Income-based Gini	-0.186***	0.011		-0.206***	-0.079*	
	(0.043)	(0.013)		(0.059)	(0.043)	
Light-based Gini	-0.152***	0.040***	0.031***	-0.272***	0.036**	0.034**
	(0.032)	(0.011)	(0.011)	(0.063)	(0.018)	(0.017)
Observations	3013	3013	3780	3013	3013	3780
# of countries	170	170	181	170	170	181
Country fixed effects	no	yes	yes	no	yes	yes
Population weights	no	no	no	yes	yes	yes

Notes: Each coefficient is a separate regression with Chinn-Ito index as explanatory.

- Once financial markets open up, tax evasion and shadow economy activities are likely to increase – income-based measures are unable to capture these effects.

Conclusions

- Lack of consistent and globally available measure of inequality.
- New measure of inequality based on geospatial data on nighttime light emissions and gridded population counts.
- Balanced sample of 234 countries/territories from 1992 to 2013.
- Measure significantly correlated with income inequality across countries, but capturing different dynamics.
    - Our conjecture: consumption, informal activities, infrastructure, wealth.
- Applications show similar cross-country, but different within-country results for income- and light-based measures.

Thank you for your attention and comments.

- Our inequality measures can be accessed through NASA SEDAC webpage: https://www.ciesin.columbia.edu/data/global-geospatial-inequality/

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Light-based Ginis over Time

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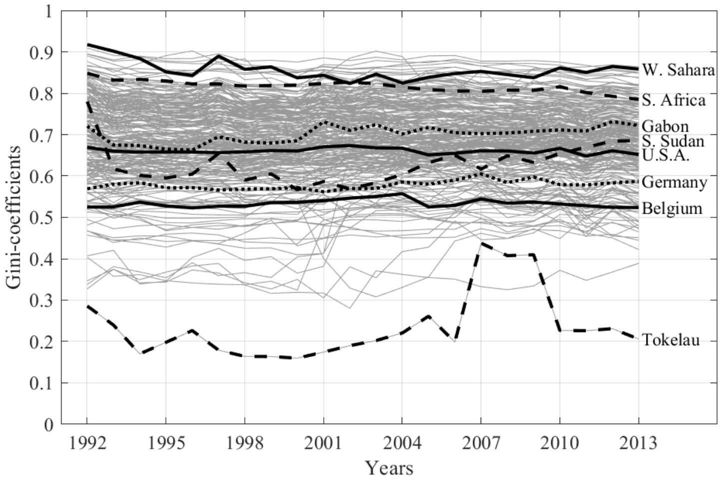

Cross-Country Data Summary Statistics

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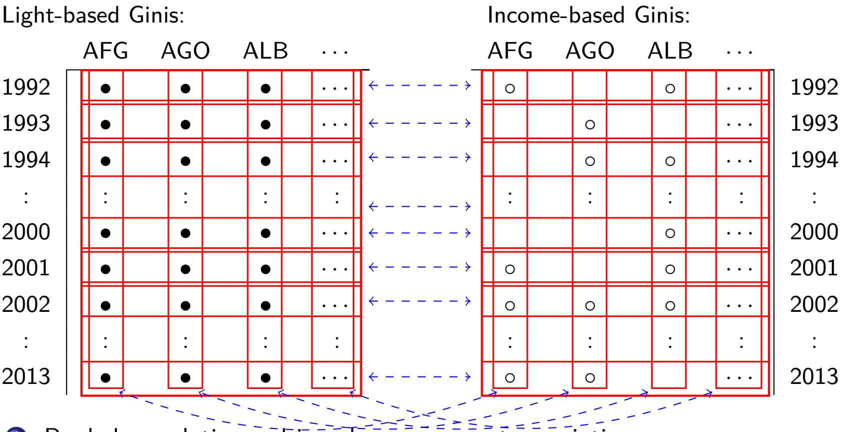
	Min	Quartiles			Max
		Q25	Q50	Q75	
Avg. cloud-free obs. per pixel (OLS)	6.42 Greenland	39.53 Colombia	50.18 Norfolk Isl.	58.03 Qatar	74.84 Mauritius
Fraction unlit pixels (OLS stable lights DN=0)	0 Singapore†	0.27 Switzerland	0.75 Norway	0.95 Gambia	1.00 Tokelau
Pop. share in unlit pixels (LSC pop., OLS stable lights DN=0)	0 Singapore†	0.03 Portugal	0.19 Colombia	0.57 Gabon	1.00 Tokelau
Fraction top-coded pixels (OLS DN=63)	0 Liberia†	0 Fiji†	0.0002 Macedonia	0.0014 Tunisia	0.578 Singapore
Pop. share in top-coded pixels (LSC pop., OLS DN=63)	0 Guinea†	0 Somalia†	0.040 Namibia	0.163 Russia	0.922 Bahrain
N. census areas (GPW)	2 Norfolk Isl.†	29 Botswana	153 Nicaragua	739 Nigeria	10.5M U.S.A.
N. populated pixels (LSC)	9 Monaco	3032 W. Samoa	78,047 Oman	368,626 Cote d'Ivoire	9.1M China

Correlations Across and Within Countries



1. Pooled correlations: driven by cross-country variation.
2. Cross-country correlations by year.
3. Within-country correlations by country.

Geospatial Gini-coefficients – Summary Statistics

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(a) LSC/Pixel-level Gini-Coefficients

	$\kappa = 0.5$	$\kappa = 1.0$	$\kappa = 1.5$	$\kappa = 2.0$	$\kappa = 3.0$	$\kappa = 5.0$
Averages	0.788	0.757	0.729	0.714	0.751	0.818
Standard deviations:						
Pooled observations	0.103	0.095	0.086	0.081	0.092	0.114
Across country averages	0.086	0.079	0.071	0.067	0.080	0.104
Across year averages	0.025	0.022	0.018	0.015	0.012	0.007

(b) GPW/Census-level Gini-Coefficients

	$\kappa = 0.5$	$\kappa = 1.0$	$\kappa = 1.5$	$\kappa = 2.0$	$\kappa = 3.0$	$\kappa = 5.0$
Averages	0.600	0.538	0.475	0.443	0.510	0.627
Standard deviations:						
Pooled observations	0.195	0.201	0.197	0.180	0.177	0.212
Across country averages	0.194	0.200	0.195	0.177	0.172	0.207
Across year averages	0.003	0.006	0.009	0.008	0.012	0.011

Estimated Weights

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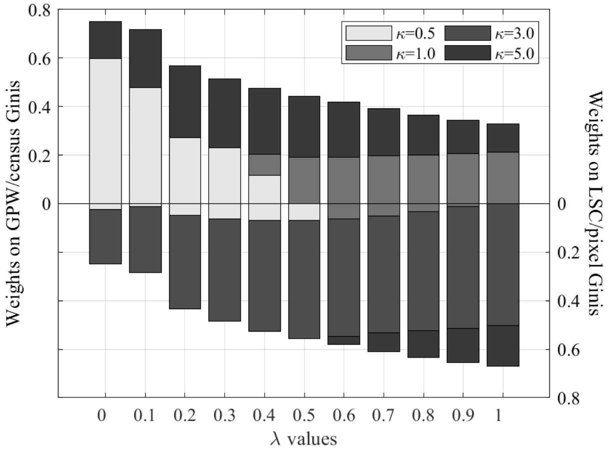

- Census-level GPW-based Ginis receive greater weight when targeting within correlation.
- $\lambda = 0.5$ provides balanced weights, with interesting correlations trade-off.

Weighted Light-based Gini-coefficients – Summary Statistics

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	Income	Weighted light-based Gini-coefficients					
		Common sample			Extended sample		
	Ginis	$\lambda = 0$	$\lambda = 0.5$	$\lambda = 1$	$\lambda = 0$	$\lambda = 0.5$	$\lambda = 1$
Averages	0.389	0.642	0.682	0.703	0.677	0.705	0.721
Standard deviations:							
Pooled observations	0.084	0.136	0.104	0.098	0.109	0.082	0.078
Across country averages	0.081	0.136	0.100	0.093	0.115	0.083	0.077
Across year averages	0.007	0.003	0.007	0.006	0.005	0.007	0.007

Cross-country Variation in Measured Inequality by Area

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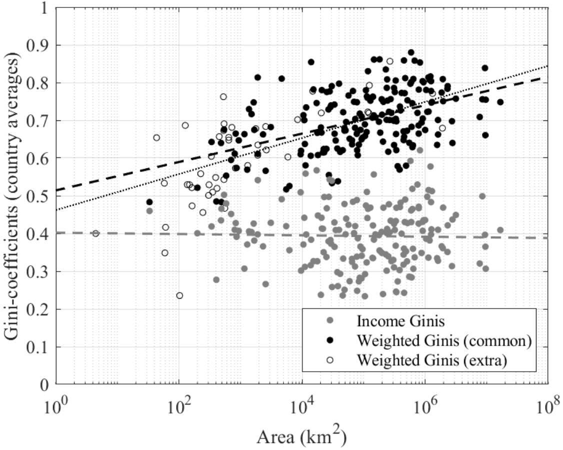

- Light-based Ginis lower for smaller countries.
- Not the case with income-based Ginis.

Cross-country Variation in Measured Inequality by Lights/Area

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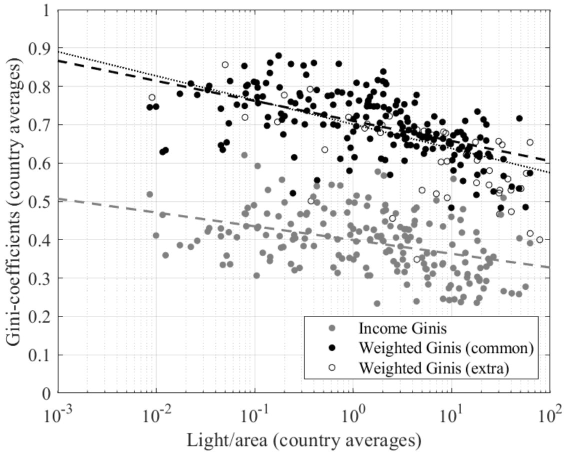

- Lights/area as proxy to development.
- Inequality is lower in more developed countries.

OOP Health Care Expenditure and Inequality

- Literature:
  - OOP health expenditures lead to financial hardship and poverty in developing countries (Xu et al., 2018).
  - OOP health expenditures increase inequality in the US (Christopher et al., 2018).
- We use WHO (2019) data on the share of OOP expenditures relative to total health expenditures.
  - Data only available for some countries starting from 2000.

Summary Statistics

OOP Health Care Expenditure and Inequality

Robustness

Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Income-based Gini	0.735*	0.145		1.463***	-0.091	
	(0.403)	(0.120)		(0.541)	(0.212)	
Light-based Gini	1.002***	0.066	-0.004	1.779***	0.589**	0.537*
	(0.279)	(0.144)	(0.137)	(0.473)	(0.292)	(0.311)
Observations	2089	2089	2601	2089	2089	2601
# of countries	177	177	188	177	177	188
Country fixed effects	no	yes	yes	no	yes	yes
Population weights	no	no	no	yes	yes	yes

Note: Each coefficient is a separate regression with OOP share (2000-2013) as explanatory.

- Lights data captures more than income:
  - OOP might not affect distribution of *income*, but composition of *expenditures*.

Robustness to λ – OOP health expenditure

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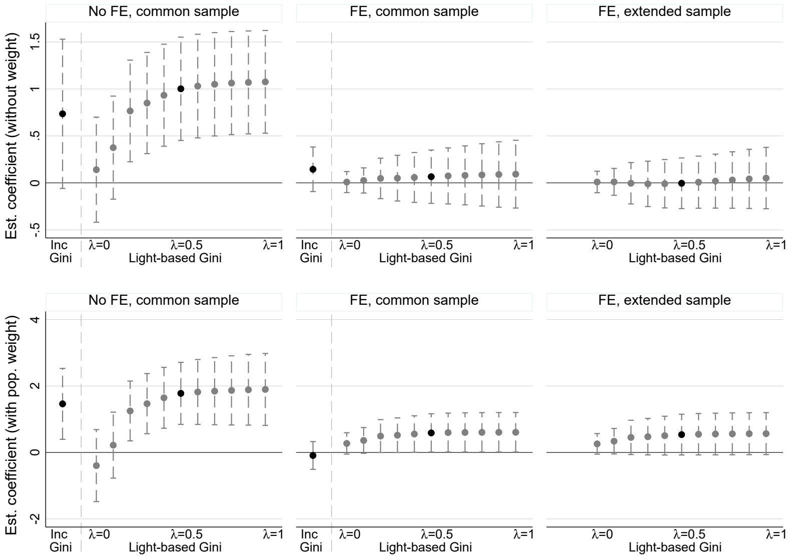

Robustness to λ – Epidemics

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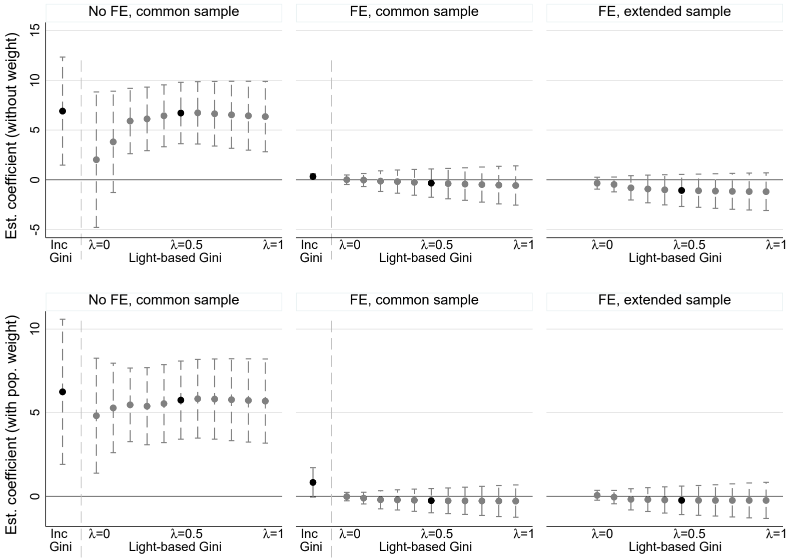

Robustness to λ – Liberalization

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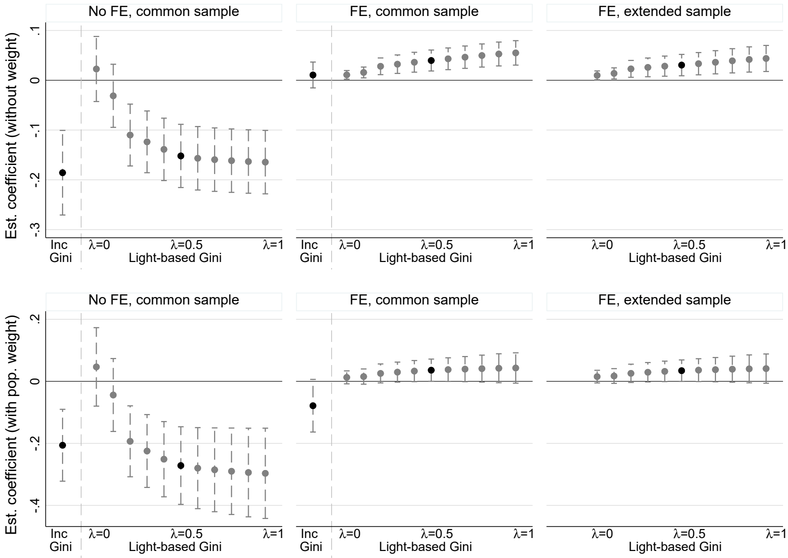

Descriptive Statistics of Application Variables

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Variable	Obs	Mean	Std. Dev.	Min	P25	P50	P75	Max
Share of OOP health exp	2601	.3503	.1999	0	.1813	.3304	.4992	.9081
Perc. of inh. affected by epi.	5148	.0004	.0061	0	0	0	0	.261
Capital account liberalization	3780	.232	1.56	-1.9166	-1.21	-.1412	2.0904	2.3467

Regression Results without Controlling for Country Area

	OOP Expenditure		Epidemics		CA Liberalization	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)
Income-based Gini	0.732*	1.442***	6.827**	5.761***	-0.186***	-0.210***
	(0.402)	(0.529)	(2.723)	(1.959)	(0.0431)	(0.0583)
Light-based Gini	0.990***	1.738***	6.433***	4.287**	-0.153***	-0.298***
	(0.280)	(0.509)	(1.637)	(2.136)	(0.0327)	(0.0773)
Observations	2089	2089	3278	3278	3013	3013
# of countries	177	177	187	187	177	188
Country fixed effects	no	no	no	no	no	no
Population weights	no	yes	no	yes	no	yes

List of Countries and Territories

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Country or territory	# inc	Country or territory	# inc	Country or territory	# inc	Country or territory	# inc	Country or territory	# inc
Afghanistan	6	Congo	7	Iceland	22	Myanmar	4	Slovakia	22
Aland Islands	0	Cook Islands	0	India	21	Namibia	21	Slovenia	22
Albania	17	Costa Rica	22	Indonesia	22	Nauru	1	Solomon Islands	9
Algeria	20	Cote d'Ivoire	22	Iran (Islamic Republic of)	22	Nepal	19	Somalia	1
American Samoa	0	Croatia	22	Iraq	7	Netherlands	22	South Africa	22
Andorra	0	Cuba	0	Ireland	22	New Caledonia	0	South Sudan	1
Angola	10	Curacao	0	Isle of Man	0	New Zealand	22	Spain	22
Antigua and Barbuda	1	Cyprus	22	Israel	22	Nicaragua	21	Sri Lanka	22
Argentina	22	Czech Republic	22	Italy	22	Niger	22	State of Palestine	16
Armenia	22	Denmark	22	Jamaica	13	Nigeria	19	Sudan	18
Aruba	0	Djibouti	18	Japan	22	Niue	0	Suriname	7
Australia	22	Dominica	9	Jersey	0	Norfolk Island	0	Swaziland	18
Austria	22	Dominican Republic	22	Jordan	22	Northern Mariana Islands	0	Sweden	22
Azerbaijan	17	DPR Korea	0	Kazakhstan	22	Norway	22	Switzerland	22
Bahamas	13	DR Congo	9	Kenya	16	Oman	0	Syrian Arab Republic	11
Bahrain	0	Ecuador	22	Kiribati	1	Pakistan	22	Taiwan	22
Bangladesh	22	Egypt	22	Kosovo	11	Palau	1	Tajikistan	22
Barbados	19	El Salvador	22	Kuwait	1	Panama	22	Thailand	22
Belarus	22	Equatorial Guinea	1	Kyrgyzstan	22	Papua New Guinea	14	Timor-Leste	13
Belgium	22	Eritrea	0	Lao PDR	22	Paraguay	22	Togo	9
Belize	17	Estonia	22	Latvia	22	Peru	22	Tokelau	0
Benin	12	Ethiopia	19	Lebanon	18	Philippines	22	Tonga	18
Bermuda	0	Faeroe Islands	0	Lesotho	19	Poland	22	Trinidad and Tobago	14
BES islands	0	Falkland Islands	0	Liberia	9	Portugal	22	Tunisia	21
Bhutan	10	Fiji	22	Libya	1	Puerto Rico	22	Turkey	22
Bolivia	22	Finland	22	Liechtenstein	0	Qatar	22	Turkmenistan	14
Bosnia and Herzegovina	13	France	22	Lithuania	22	Republic of Korea	22	Turks and Caicos Islands	1
Botswana	19	French Guiana	0	Luxembourg	22	Republic of Moldova	22	Tuvalu	17
Brazil	22	French Polynesia	0	Madagascar	21	Republic of North Macedonia	20	Uganda	22
British Virgin Islands	0	Gabon	1	Malawi	22	Reunion	0	Ukraine	22
Brunei Darussalam	0	Gambia	22	Malaysia	22	Romania	22	United Arab Emirates	1
Bulgaria	22	Georgia	22	Maldives	9	Russian Federation	22	United Kingdom	22
Burkina Faso	20	Germany	22	Mali	16	Rwanda	22	United Republic of Tanzania	22
Burundi	22	Ghana	22	Malta	15	Saint Helena	0	United States of America	22
Cambodia	16	Greece	22	Marshall Islands	0	Saint Kitts and Nevis	10	Uruguay	22
Cameroon	18	Greenland	0	Martinique	0	Saint Lucia	13	US Virgin Islands	0
Canada	22	Grenada	10	Mauritania	22	Saint Pierre and Miquelon	0	Uzbekistan	12
Cape Verde	15	Guadeloupe	0	Mauritius	21	Saint Vincent	14	Vanuatu	5
Cayman Islands	0	Guam	0	Mayotte	0	San Marino	0	Venezuela	22
Central African Republic	17	Guatemala	22	Mexico	22	Sao Tome and Principe	11	Viet Nam	22
Chad	9	Guernsey	0	Micronesia	16	Saudi Arabia	0	Wallis and Futuna Islands	0
Chile	22	Guinea	21	Monaco	0	Senegal	20	Western Sahara	0
China	22	Guinea-Bissau	18	Mongolia	19	Serbia	17	Western Samoa	7
China, Hong Kong	22	Guyana	16	Montenegro	9	Seychelles	8	Yemen	22
China, Macao	0	Haiti	12	Montserrat	0	Sierra Leone	20	Zambia	22
Colombia	22	Honduras	22	Morocco	22	Singapore	22	Zimbabwe	17
Comoros	10	Hungary	22	Mozambique	18	Sint Maarten (Dutch part)	0		