ILLUMINATING SPATIAL INEQUALITY, CONVERGENCE, AND ECONOMIC DEVELOPMENT IN THE PHILIPPINES: EVIDENCE FROM HIGHER-QUALITY NIGHTTIME LIGHTS

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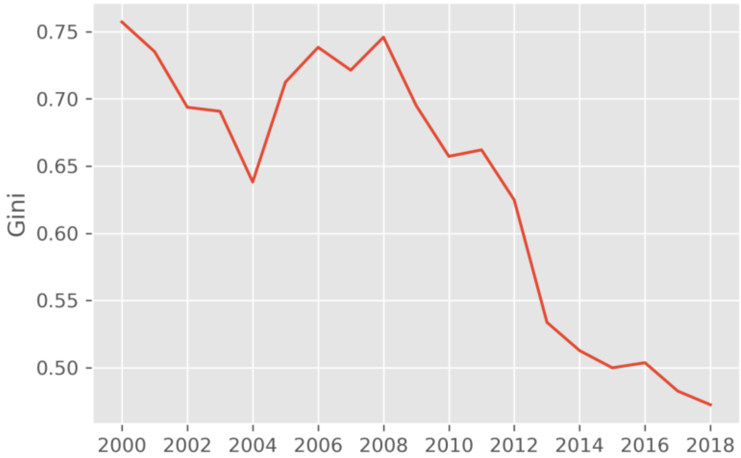
Contributions

- First, combining higher-quality nighttime lights and gridded population data, I construct measures of spatial income inequality for the Philippines and its 17 administrative regions in the period 2000-2018.
- Second, I uncover beta convergence of income per capita across provinces, with the speed of convergence around 5% and a half-life time of convergence of 20 years.
- Third, I establish a U-shaped relationship between spatial inequality and economic development at the region level, which is robust across parametric and semiparametric specifications as well as to business cycle effects.
- Fourth, I show that although structural transformation in the form of a structural shift from agriculture to modern industries and services influences spatial inequality through its effect on economic development, the strong U-shaped link between spatial inequality and economic development is above and beyond its relationship with structural transformation.

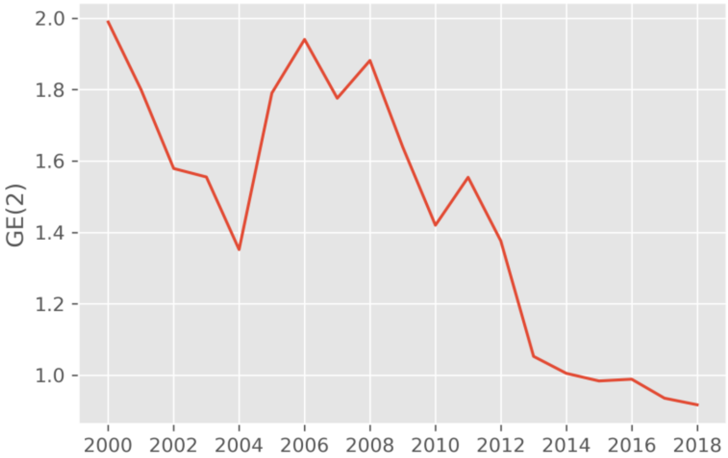
The Philippines has achieved tremendous improvements in narrowing income disparities in the period 2000-2018.

Overall inequality in the Philippines decreased in 2000-2004, increased in 2004-2008, and took a nosedive in 2008-2018. Income inequality has declined by at least 60% over the last two decades.

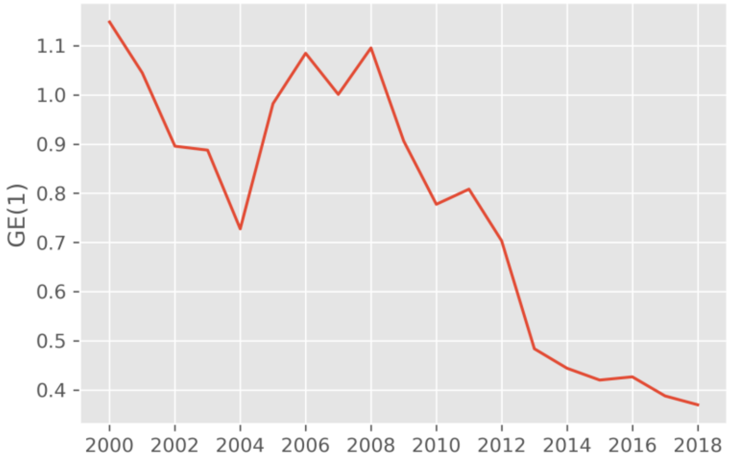
Gini coefficient



Coefficient of variation



Theil index



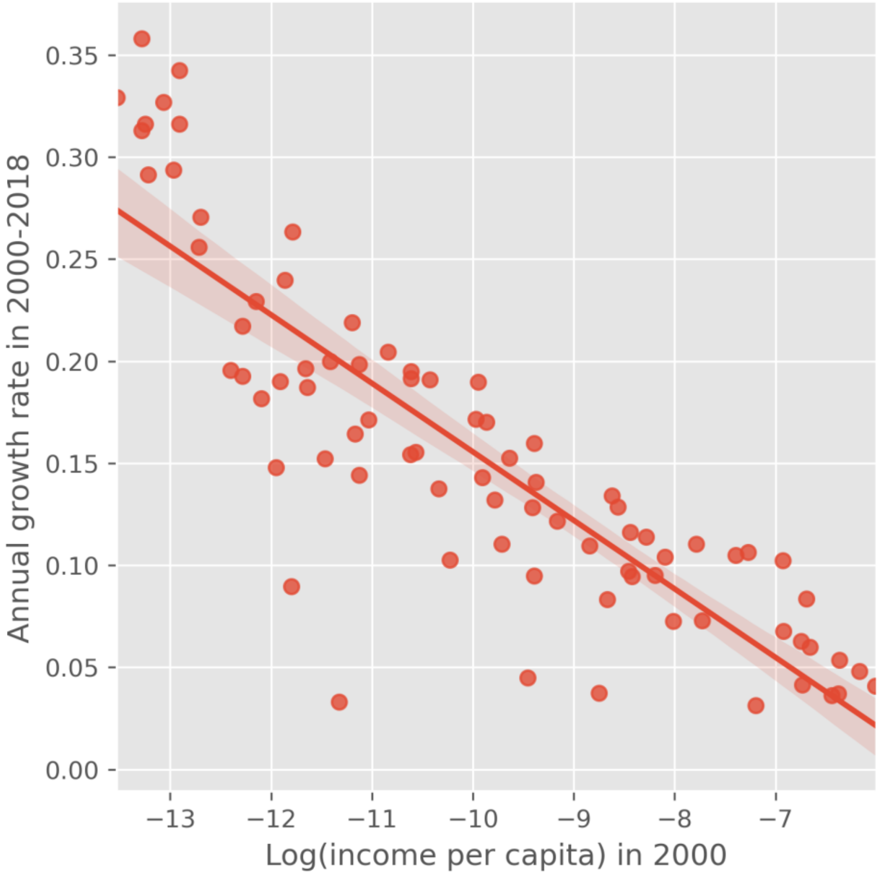
Notes: I use population shares as weights in constructing all measures of spatial inequality to account for uneven population distributions across regions.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021) and gridded population data from the Gridded Population of the World (GPW) version 4.

I find robust evidence of absolute beta convergence in income per capita across provinces in the last two decades.

On average, the poorest provinces are growing at a faster rate than the richest provinces.

Baseline sample

Excluding Metro Manila



Sources: Author's calculations using nighttime lights data of Chen et al. (2021) and gridded population data from the Gridded Population of the World (GPW) version 4.

Income per capita across provinces are converging at an annual rate of 5%, leading to a half-life time of convergence of 20 years.

Evidence of absolute beta convergence in income per capita across provinces

Baseline sample: 81 provinces and 17 cities in Metro Manila

Parameter	Value
Beta coefficient	-0.0341***
Speed of convergence	5.3%
Half-life (years)	20.0

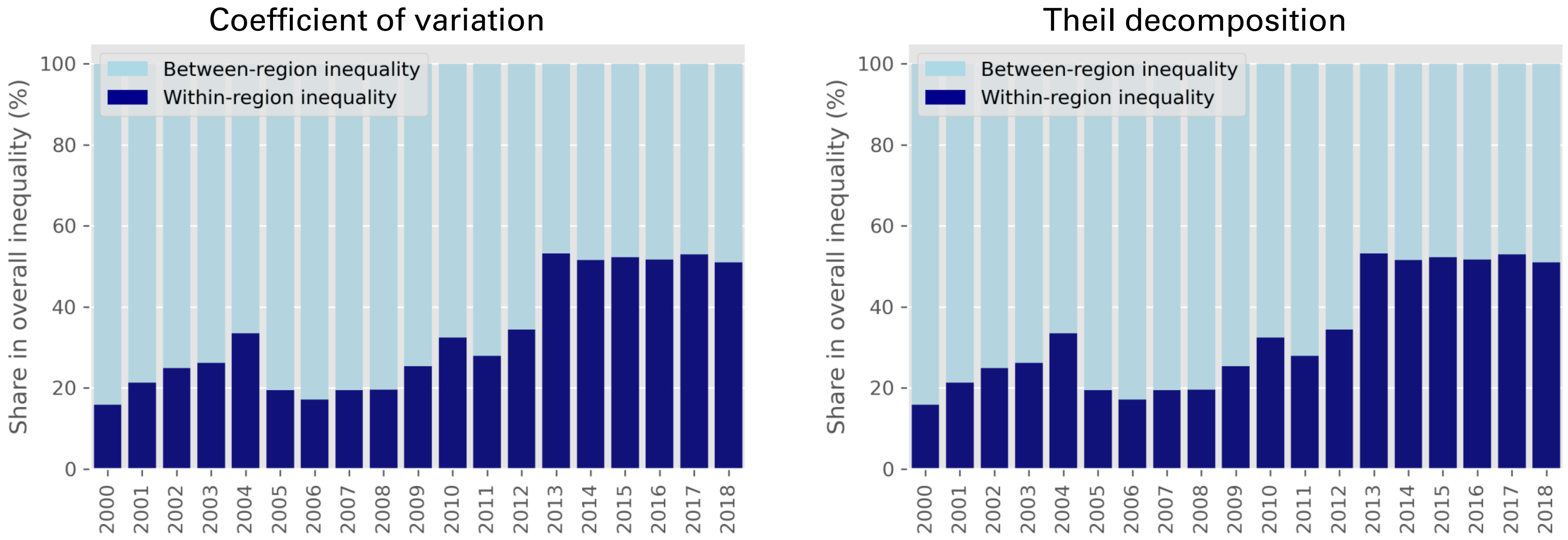
Sample excluding Metropolitan Manila as outlier

Parameter	Value
Beta coefficient	-0.0336***
Speed of convergence	5.2%
Half-life (years)	20.3

Notes: The beta coefficient is the coefficient of a linear regression given by equation #, the speed of convergence is the coefficient of a nonlinear least squares regression of equation #, which can also be calculated from the beta coefficient. The half-life is calculated using equation #. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021) and gridded population data from the Gridded Population of the World (GPW) version 4.

Despite sizable declines in spatial inequalities, however, income differences *within* regions as opposed to income disparities *between* regions has become more important in the recent years.

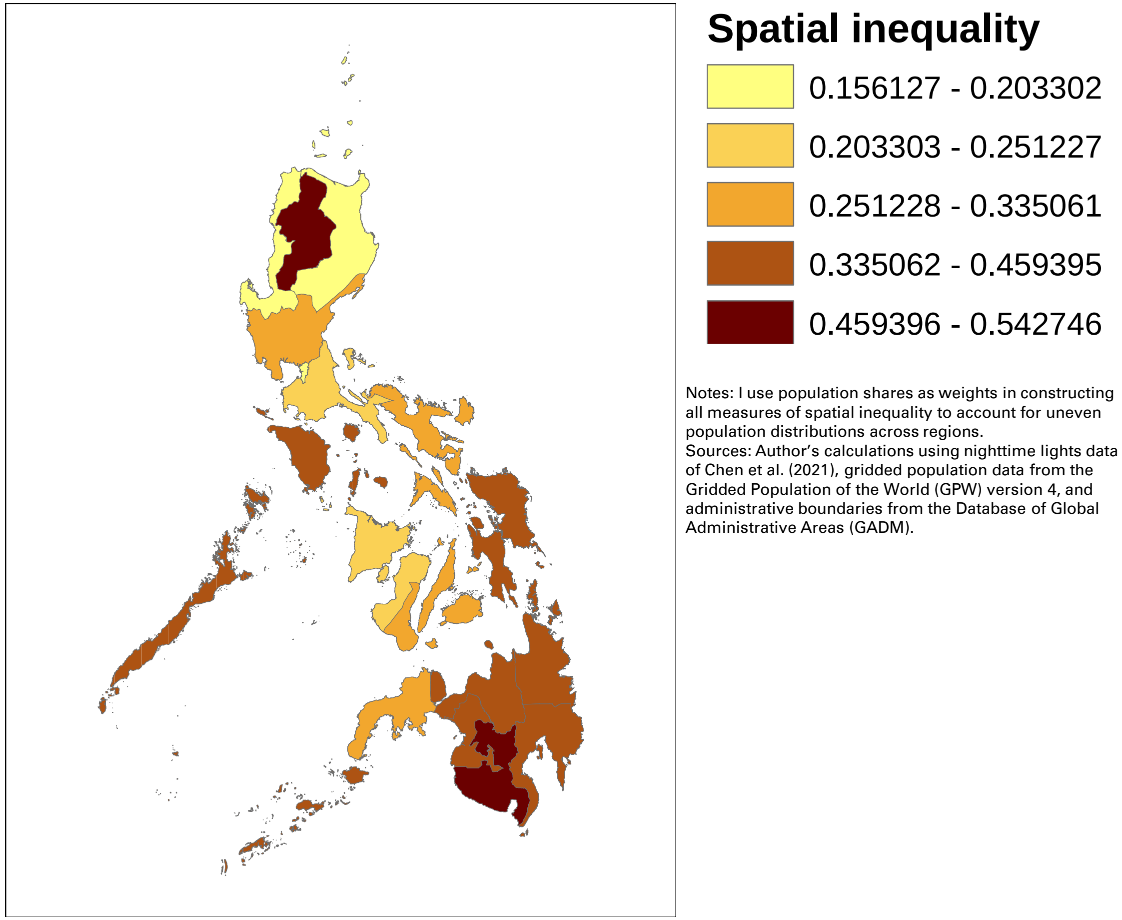
Within-region inequality accounted for less than 20% of the variation in overall inequality in 2000. Starting 2013, however, more than half of the variation in national inequality is consistently due to income disparities within regions.



Notes: I use population shares as weights in constructing all measures of spatial inequality to account for uneven population distributions across regions.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021) and gridded population data from the Gridded Population of the World (GPW) version 4.

Mapping spatial inequality in the Philippines in 2000-2018

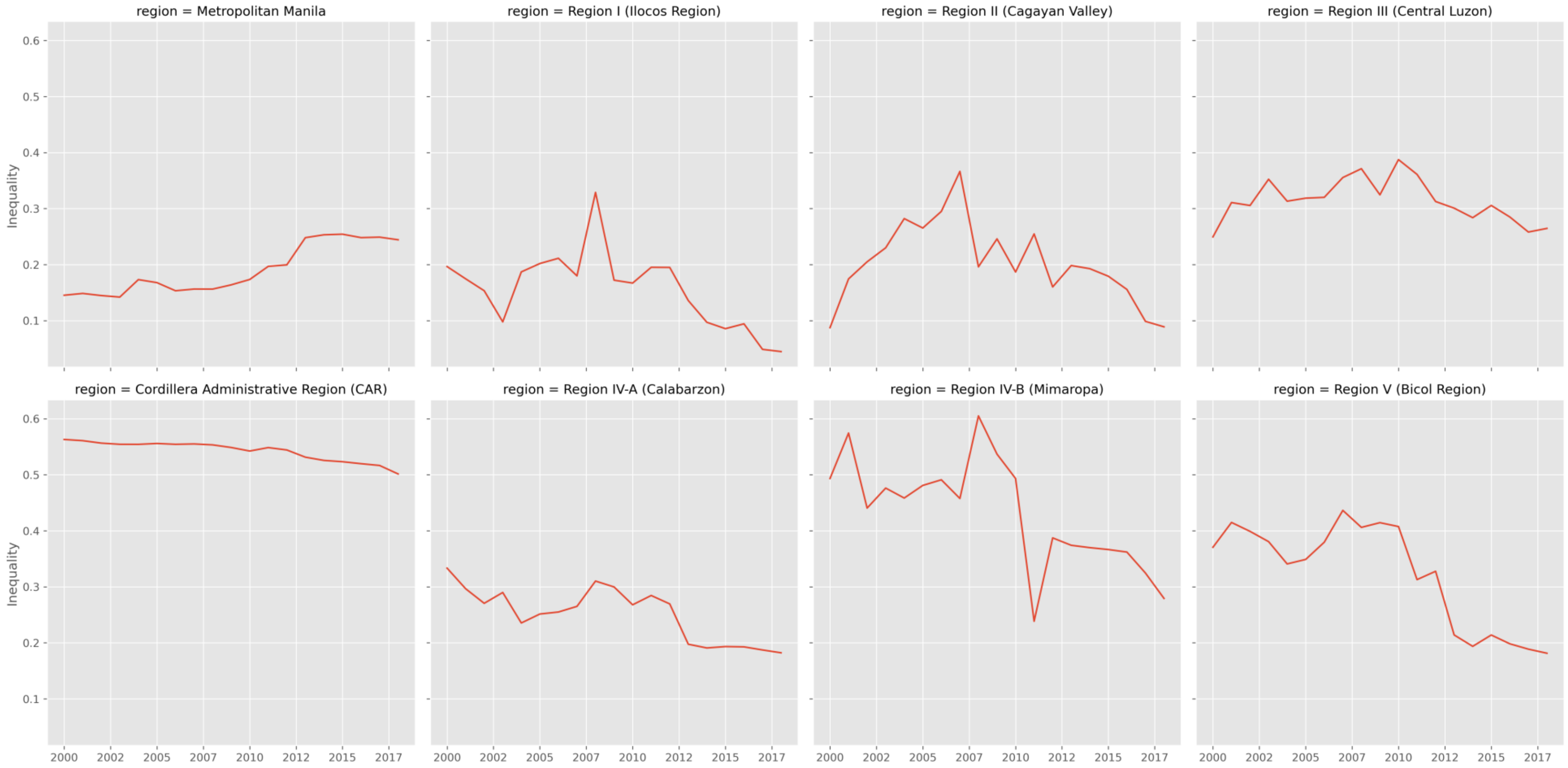
Despite sizable declines in overall inequality, income disparities continue to be substantial in Region XII (SOCCSKSARGEN), CAR, and Region X (Northern Mindanao).



Notes: I use population shares as weights in constructing all measures of spatial inequality to account for uneven population distributions across regions.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, and administrative boundaries from the Database of Global Administrative Areas (GADM).

At least 80% of the regions experienced sigma convergence in the last two decades.

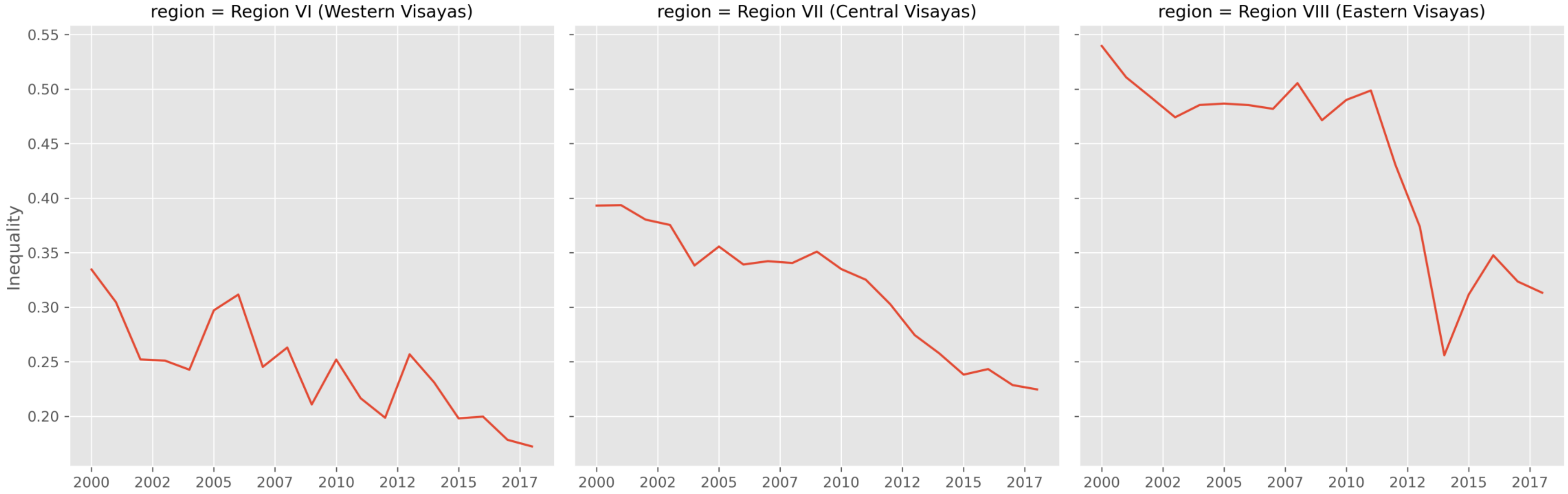
In the Luzon island, income dispersion within each of the regions narrowed. In contrast, income disparities within Metro Manila widened.



Notes: I use population shares as weights in constructing all measures of spatial inequality to account for uneven population distributions across regions. The markers are calculated measures of inequality, while the solid line is a predicted measure of inequality estimated using a local nonparametric regression.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021) and gridded population data from the Gridded Population of the World (GPW) version 4.

At least 80% of the regions experienced sigma convergence in the last two decades.

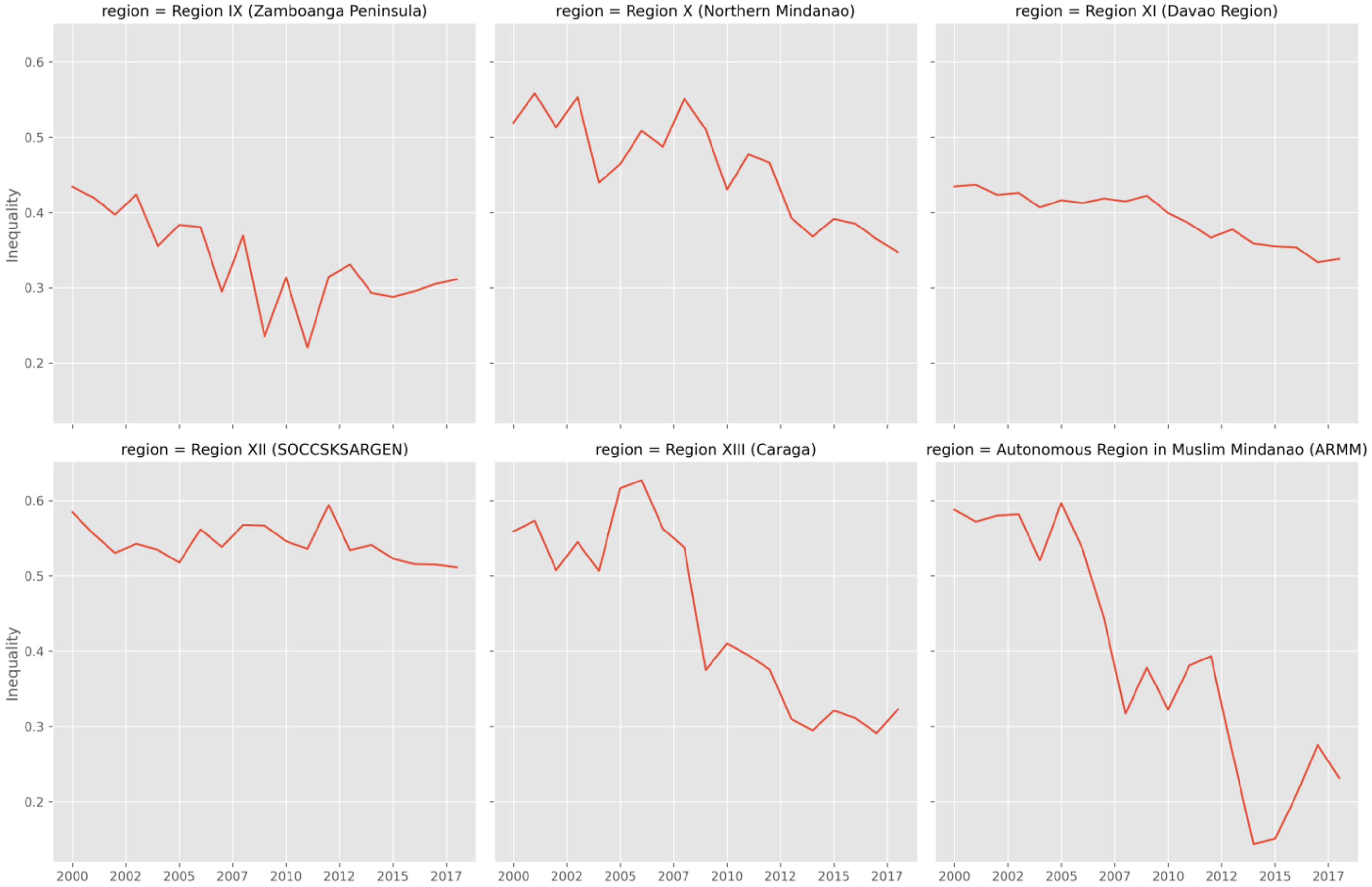
In the Visayas island, income dispersion within each of the regions also tapered.



Notes: I use population shares as weights in constructing all measures of spatial inequality to account for uneven population distributions across regions. The markers are calculated measures of inequality, while the solid line is a predicted measure of inequality estimated using a local nonparametric regression.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021) and gridded population data from the Gridded Population of the World (GPW) version 4.

At least 80% of the regions experienced sigma convergence in the last two decades.

In the Mindanao island, income dispersion within each of the regions also contracted.



Notes: I use population shares as weights in constructing all measures of spatial inequality to account for uneven population distributions across regions. The markers are calculated measures of inequality, while the solid line is a predicted measure of inequality estimated using a local nonparametric regression.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021) and gridded population data from the Gridded Population of the World (GPW) version 4.

During the course of regional development, income disparities within regions first decreases, reaches a trough, and then increases, thus following a U-shaped trajectory.

Fixed effects regression of spatial inequality on GDP per capita and square of GDP per capita

	Baseline sample			Excluding Metro Manila		
Y = Gini coefficient	(1)	(2)	(3)	(4)	(5)	(6)
Log(GDP per capita)	0.14	-2.63***	-2.25***	0.08	-3.11***	-3.05***
Square of Log(GDP per capita)		0.13***	0.11***		0.15***	0.15***
Urbanization			-0.003			-0.004
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of regions	17	17	17	16	16	16
No. of years	19	19	19	19	19	19
No. of observations	313	313	313	294	294	294
Within R-squared	0.45	0.57	0.58	0.53	0.58	0.59

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, gross regional domestic product and census population data from the Philippine Statistics Authority.

This finding is robust to the sensitivity of the spatial inequality measure to income differences in both tails of the income distribution.

Fixed effects regression of inequality on GDP per capita and square of GDP per capita

	Baseline sample			Excluding Metro Manila		
Y = Coefficient of variation	(1)	(2)	(3)	(4)	(5)	(6)
Log(GDP per capita)	0.30	-5.48***	-4.70***	0.16	-5.90**	-5.80**
Square of Log(GDP per capita)		0.27***	0.23***		0.29**	0.28**
Urbanization			-0.01			-0.01
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of regions	17	17	17	16	16	16
No. of years	19	19	19	19	19	19
No. of observations	313	313	313	294	294	294
Within R-squared	0.43	0.55	0.56	0.51	0.56	0.57

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, gross regional domestic product and census population data from the Philippine Statistics Authority.

This finding is robust to the sensitivity of the spatial inequality measure to income differences in both tails of the income distribution.

Fixed effects regression of inequality on GDP per capita and square of GDP per capita

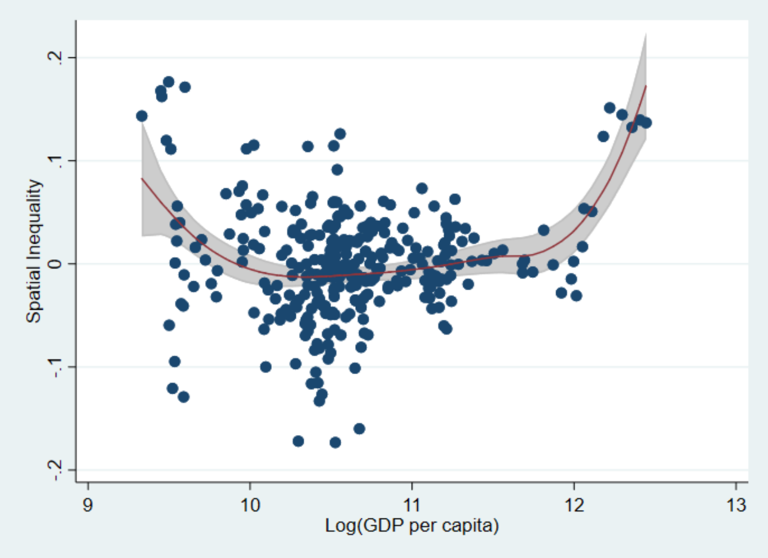
	Baseline sample			Excluding Metro Manila		
Y = Theil index	(1)	(2)	(3)	(4)	(5)	(6)
Log(GDP per capita)	0.26	-3.43***	-3.52**	0.18	-4.59*	-4.58*
Square of Log(GDP per capita)		0.17***	0.17**		0.23*	0.23*
Urbanization			-0.001			-0.004
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of regions	17	17	17	16	16	16
No. of years	19	19	19	19	19	19
No. of observations	313	313	313	294	294	294
Within R-squared	0.50	0.57	0.57	0.54	0.58	0.57

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, gross regional domestic product and census population data from the Philippine Statistics Authority.

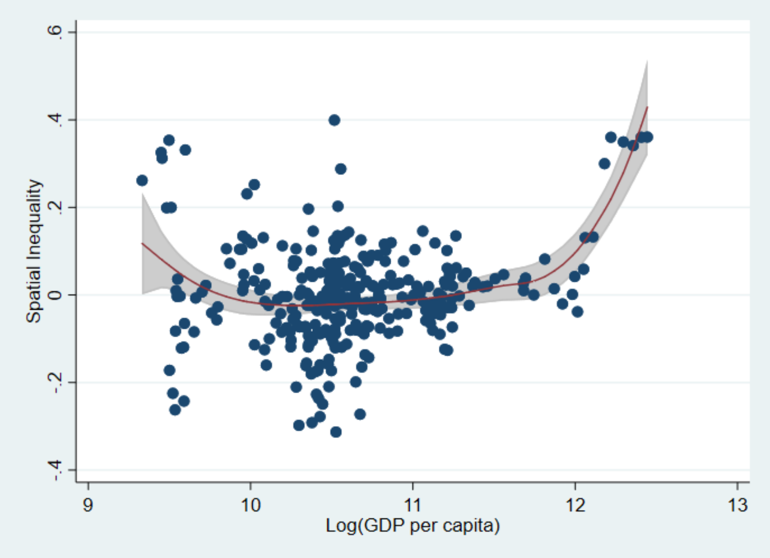
Semiparametric estimation confirms the U-shaped relationship between spatial inequality and regional economic development.

Fixed effects semiparametric regression of spatial inequality on GDP per capita

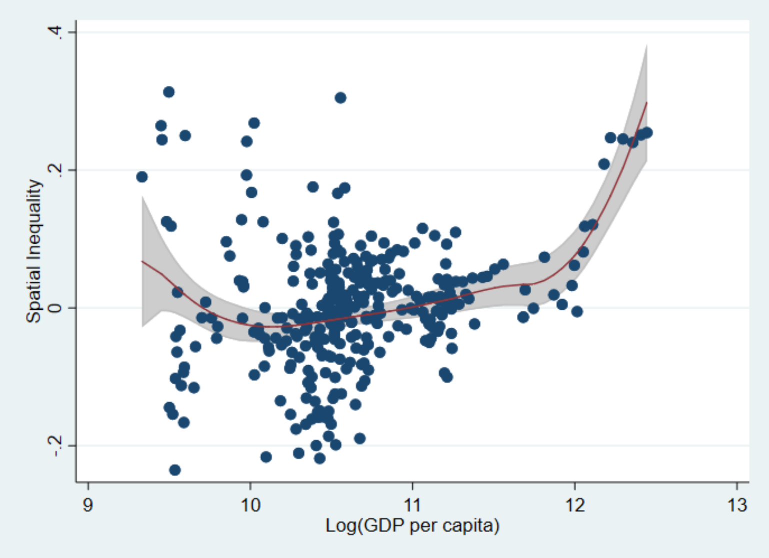
Gini coefficient



Coefficient of variation



Theil Index



Notes: Kernel=epanechnikov. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, gross regional domestic product and census population data from the Philippine Statistics Authority.

The structural shift from agriculture to modern industries and services tends to narrow income disparities within regions, but it also promotes inequalities as regions further industrialize.

Fixed effects regression of inequality on non-agriculture GVA and square of non-agriculture GVA

	Baseline sample			Excluding Metro Manila		
Y = Gini coefficient	(1)	(2)	(3)	(4)	(5)	(6)
Share of non-agriculture GVA	-0.36	-3.54***	-2.54***	-0.12	-2.81**	-2.58**
Square of share of non-agriculture GVA		2.12***	1.43**		1.78**	1.60**
Urbanization			-0.006			-0.002
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of regions	17	17	17	16	16	16
No. of years	19	19	19	19	19	19
No. of observations	305	305	305	286	286	286
Within R-squared	0.44	0.50	0.53	0.52	0.56	0.56

Notes: GVA=gross value added. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, gross regional domestic product and census population data from the Philippine Statistics Authority.

This result remains consistent across different measures of spatial inequality.

Fixed effects regression of inequality on non-agriculture GVA and square of non-agriculture GVA

	Baseline sample			Excluding Metro Manila		
Y = Coefficient of variation	(1)	(2)	(3)	(4)	(5)	(6)
Share of non-agriculture GVA	-0.92	-6.97**	-4.82*	-0.39	-5.38**	-4.92**
Square of share of non-agriculture GVA		4.03**	2.55		3.30**	2.93*
Urbanization			-0.012			-0.004
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of regions	17	17	17	16	16	16
No. of years	19	19	19	19	19	19
No. of observations	305	305	305	286	286	286
Within R-squared	0.42	0.47	0.51	0.51	0.54	0.54

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, gross regional domestic product and census population data from the Philippine Statistics Authority.

Once conditioned on economic development, structural transformation loses its power in influencing spatial inequality…

Fixed effects regression of inequality on non-agriculture GVA and GDP per capita

	Baseline sample			Excluding Metro Manila		
Y = Gini coefficient	(1)	(2)	(3)	(4)	(5)	(6)
Share of non-agriculture GVA	-3.54***	-2.06*	-1.87	-2.81**	-1.98*	-1.69
Square of share of non-agriculture GVA	2.12***	1.34*	1.18*	1.78**	1.32*	1.09*
Log(GDP per capita)		-2.41***	-2.13***		-2.56***	-2.56***
Square of Log(GDP per capita)		0.11***	0.10***		0.12***	0.12***
Urbanization			-0.002			-0.002
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of regions	17	17	17	16	16	16
No. of years	19	19	19	19	19	19
No. of observations	305	305	305	286	286	286
Within R-squared	0.50	0.58	0.58	0.56	0.59	0.59

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author’s calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, gross regional domestic product and census population data from the Philippine Statistics Authority.

…which implies that structural transformation influences spatial inequality through its effect on economic development.

Fixed effects regression of inequality on non-agriculture GVA and GDP per capita

	Baseline sample			Excluding Metro Manila		
Y = Coefficient of variation	(1)	(2)	(3)	(4)	(5)	(6)
Share of non-agriculture GVA	-6.97**	-3.80	-3.33	-5.38**	-3.80*	-3.17
Square of share of non-agriculture GVA	4.03**	2.35	1.97	3.30**	2.41	1.93
Log(GDP per capita)		-4.94***	-4.26***		-4.66**	-4.65**
Square of Log(GDP per capita)		0.24***	0.20***		0.22**	0.22**
Urbanization			-0.005			-0.005
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of regions	17	17	17	16	16	16
No. of years	19	19	19	19	19	19
No. of observations	305	305	305	286	286	286
Within R-squared	0.47	0.56	0.56	0.54	0.56	0.57

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author’s calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, gross regional domestic product and census population data from the Philippine Statistics Authority.

As further robustness checks, I show that the U-shaped relationship between spatial inequality and economic development is robust to business cycle effects.

Fixed effects regression of inequality on GDP per capita and square of GDP per capita

	5-year average			Excluding Metro Manila		
Y = Gini coefficient	(1)	(2)	(3)	(4)	(5)	(6)
Log(GDP per capita)	0.18	-2.63***	-2.22**	0.10	-3.22***	-3.18**
Square of Log(GDP per capita)		0.13***	0.11***		0.16***	0.15**
Urbanization			-0.003			-0.004
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of regions	17	17	17	16	16	16
No. of periods	4	4	4	4	4	4
No. of observations	66	66	66	62	62	62
Within R-squared	0.59	0.74	0.74	0.67	0.74	0.76

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, gross regional domestic product and census population data from the Philippine Statistics Authority.

To partial out business cycle effects, I use 5-year averages of the data. The result remains robust across different measures of spatial inequality.

Fixed effects regression of inequality on GDP per capita and square of GDP per capita

	5-year average			Excluding Metro Manila		
Y = Coefficient of variation	(1)	(2)	(3)	(4)	(5)	(6)
Log(GDP per capita)	0.27	-5.51***	-4.69**	0.20	-6.13**	-6.04**
Square of Log(GDP per capita)		0.27***	0.23***		0.30**	0.29**
Urbanization			-0.006			-0.007
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of regions	17	17	17	16	16	16
No. of periods	4	4	4	4	4	4
No. of observations	66	66	66	62	62	62
Within R-squared	0.63	0.70	0.71	0.65	0.71	0.72

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, gross regional domestic product and census population data from the Philippine Statistics Authority.

The result remains robust across different measures of spatial inequality.

Fixed effects regression of inequality on GDP per capita and square of GDP per capita

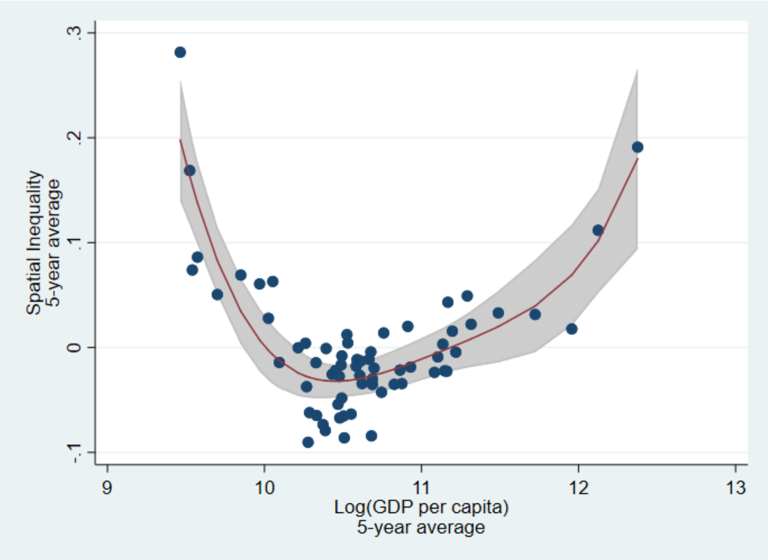
	5-year average			Excluding Metro Manila		
Y = Theil index	(1)	(2)	(3)	(4)	(5)	(6)
Log(GDP per capita)	0.30	-3.43**	-3.51*	0.21	-4.76*	-4.75*
Square of Log(GDP per capita)		0.17***	0.17**		0.23*	0.23*
Urbanization			-0.006			-0.005
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
No. of regions	17	17	17	16	16	16
No. of periods	4	4	4	4	4	4
No. of observations	66	66	66	62	62	62
Within R-squared	0.62	0.71	0.71	0.67	0.72	0.72

Notes: *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, gross regional domestic product and census population data from the Philippine Statistics Authority.

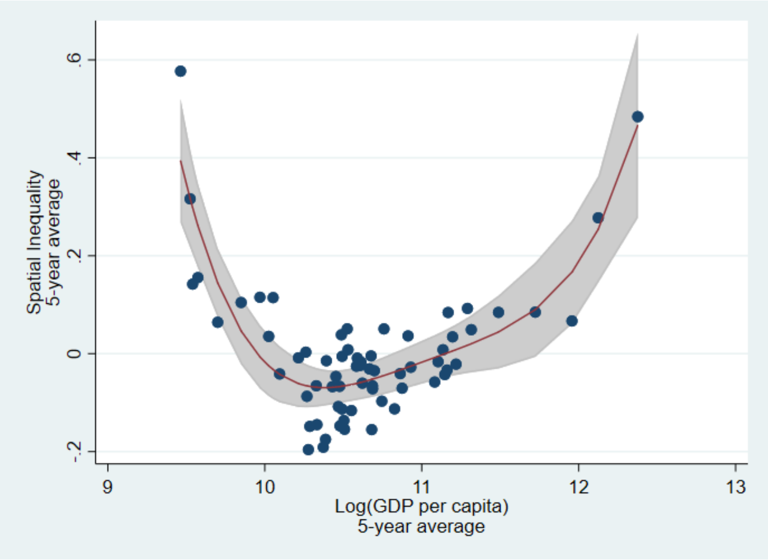
Semiparametric estimation of the model using 5-year averages results to a consistent U-shaped relationship between spatial inequality and economic development.

Fixed effects semiparametric regression of 5-year average spatial inequality on 5-year average GDP per capita to partial out business cycle effects

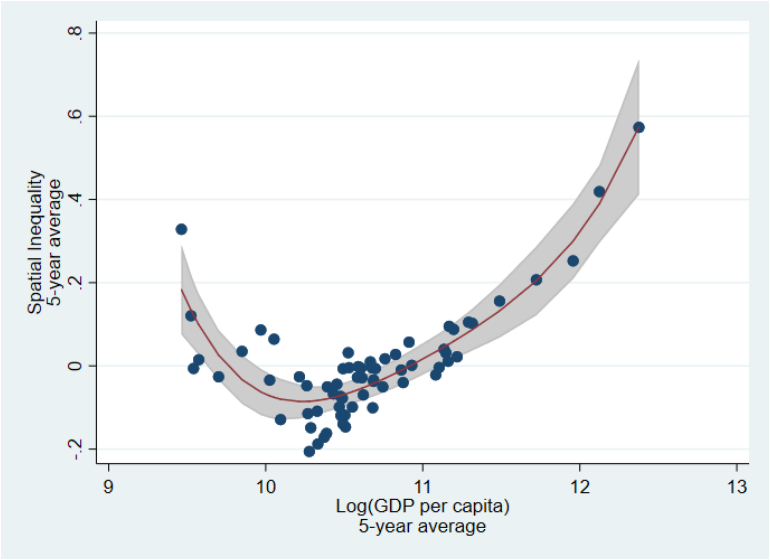
Gini coefficient



Coefficient of variation



Theil Index



Notes: Kernel=epanechnikov, Degrees=4. All standard errors are robust to cluster heteroscedasticity in the region level.
Sources: Author's calculations using nighttime lights data of Chen et al. (2021), gridded population data from the Gridded Population of the World (GPW) version 4, gross regional domestic product and census population data from the Philippine Statistics Authority.

For Future Work

- The effects of structural transformation may be heterogeneous across sub-sectors within industry and services.

- For example, geographically concentrated textiles and garments may induce greater inequality, whereas geographically dispersed food and electrical machinery may promote more income equality.

- Due to uneven distribution of natural resources, mining could contribute to spatial inequality, whereas services which tend to local markets promote greater spatial equality.

- So far, I have looked at the impact of a shift to the combined sectors of industry and services. From a policy perspective, it could also be useful to differentiate the effects across sub-sectors for a more targeted and coordinated policy design of regional development.