Regional Income Disparities, Distributional Convergence, and Spatial Effects:

Evidence from Indonesia

Carlos Mendez
Associate Professor
Graduate School of International Development Nagoya University

Anang Budi Gunawan
Doctoral Student
Graduate School of International Development, Nagoya University

Felipe Santos-Marquez
Master Student
Graduate School of International Development Nagoya University

Prepared for the Applied Regional Science Conference (ARSC) 2019 Saga, 23-24 November 2019

[Slides available at: https://quarcs-lab.rbind.io]

Motivation:

- Large regional differences in income per capita despite several policy efforts (Akita 1988; Garcia and Soelistianingsih 1998; Kataoka 2012)
- Spatial effects play a small role in provincial convergence in Indonesia (Vidyattama 2013, 2014)

Research Objective:

- Study the spatio-temporal dynamics of income per capita accross Indonesian regions using a novel district-level dataset constructed for the 2000-2017 period

Methods:

- Classical convergence (Barro and Sala-i-Martin 1992)
- Distributional convergence (Quah 1996; Hyndman et. al 1996)
- Spatial autocorrelation (Moran 1948, Anselin et. al 2006)
- Spatial decomposition (Getis 1995; Fischer and Stumpner 2010)

Data:

- 514 districts (34 provinces) over the 2000-2017 period.

Main Results:

1. On average, convergence at the provincial and district levels
2. Beyond the average, lack of distributional convergence
    - Mostly relative stagnation with some signs of divergence at the tails
3. Significant and increasing spatial autocorrelation: ONLY at the district level
4. Spatial effects play a role in the distribution dynamics
    - Spatial dependece helps reduce extreme disparities
        - It helps avoid further income polarization

Outline of this presentation

1. Some Stylized Facts
   - On average, convergence at the provincial and district levels
   - Significant and increasing spatial autocorrelation: ONLY at the district level
2. Distributional convergence and spatial decomposition frameworks
   - Distributional convergence framework (intuition)
   - Spatial decomposition framework (intution)
3. Main Results:
   - Beyond the average, lack of distributional convergence
   - Spatial dependece helps reduce extreme disparities

(1) Some Stylized Facts

On average, convergence at the provincial and district levels

Significant and increasing spatial autocorrelation: ONLY at the district level

On average, is there convergence at the provincial level?

Sigma Convergence

	Standard Deviation
Dispersion in 2000	0.70
Dispersion in 2017	0.55
Dispersion Ratio	1.27
F-Statistics	1.60
P-Value	0.18

Beta Convergence

	Annual Growth of Regional GDP Per Capita
Beta Coefficient	-0.281
Speed of Convergence	0.019
Half-life time (years)	35.17
R-Squared	0.43
P-Value of Beta	0.00

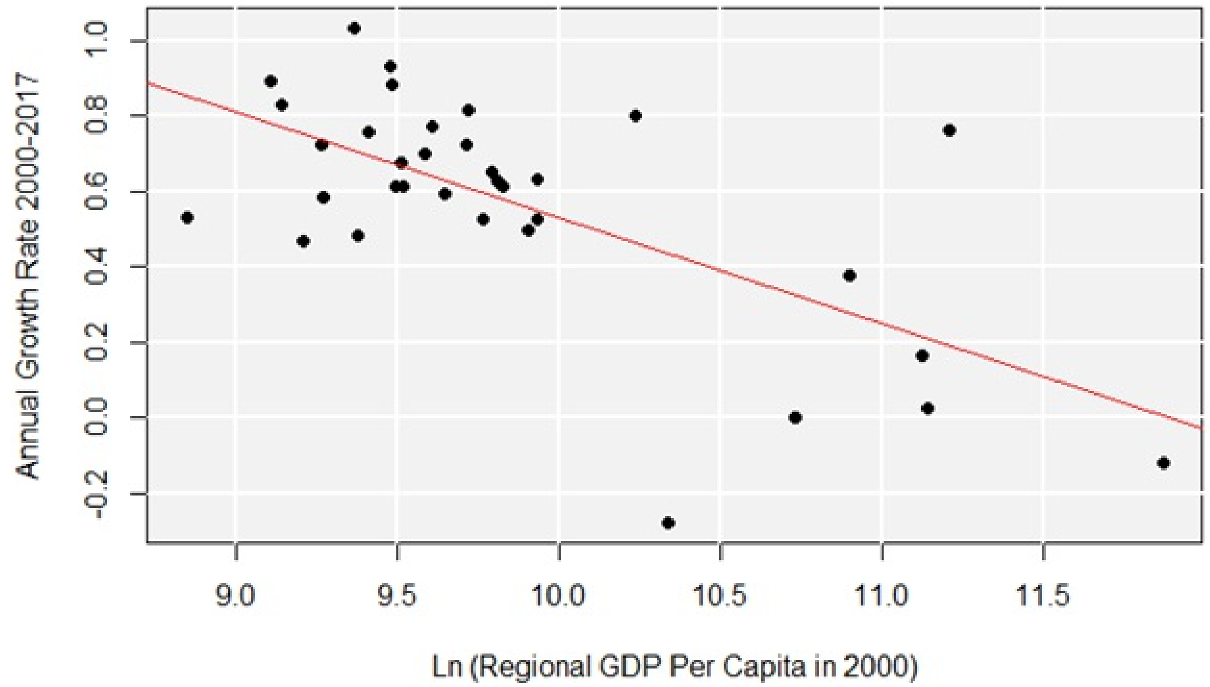


Figure 1. Beta Convergence of Regional GDP Per Capita at Provincial Level

Note : 1. For the beta convergence analysis, the regression include a constant term, which is not presented in the slide.

2. Some missing data in several new provinces are interpolated using linear regression

Source : Authors's Calculation

On average, is there convergence at the district level?

Sigma Convergence

	Standard Deviation
Dispersion in 2000	0.81
Dispersion in 2017	0.67
Dispersion Ratio	1.20
F-Statistics	1.40
P-Value	0.00

Beta Convergence

	Annual Growth of Regional GDP Per Capita
Beta Coefficient	-0.242
Speed of Convergence	0.016
Half-life time (years)	42.5
R-Squared	0.34
P-Value of Beta	0.00

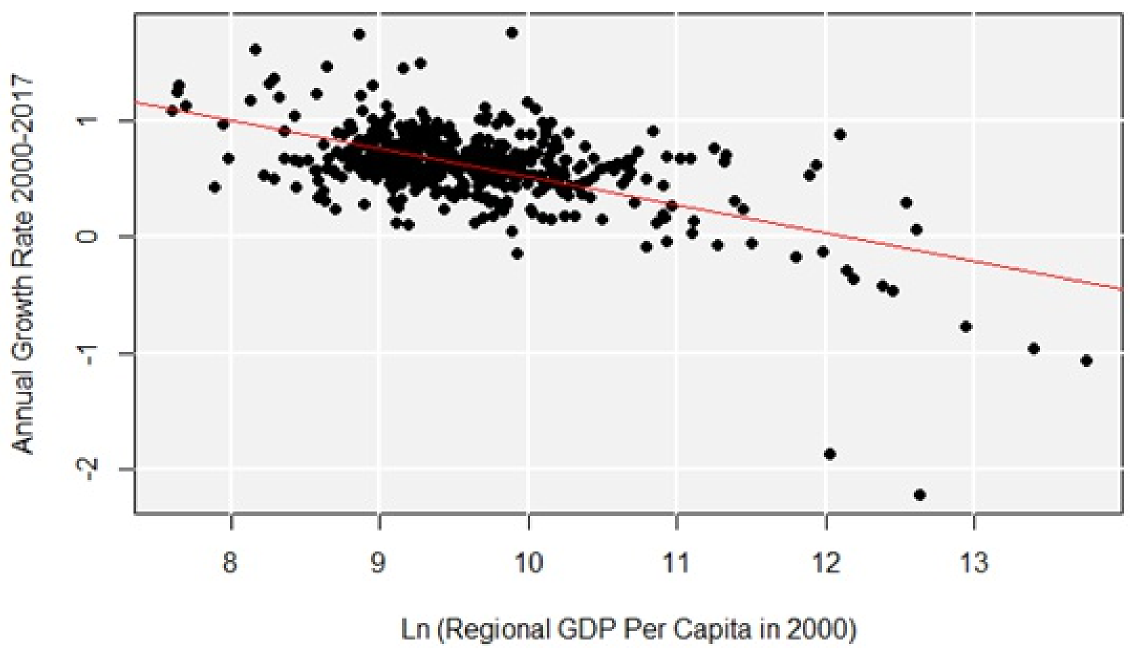


Figure 2. Beta Convergence of Regional GDP Per Capita at District Level

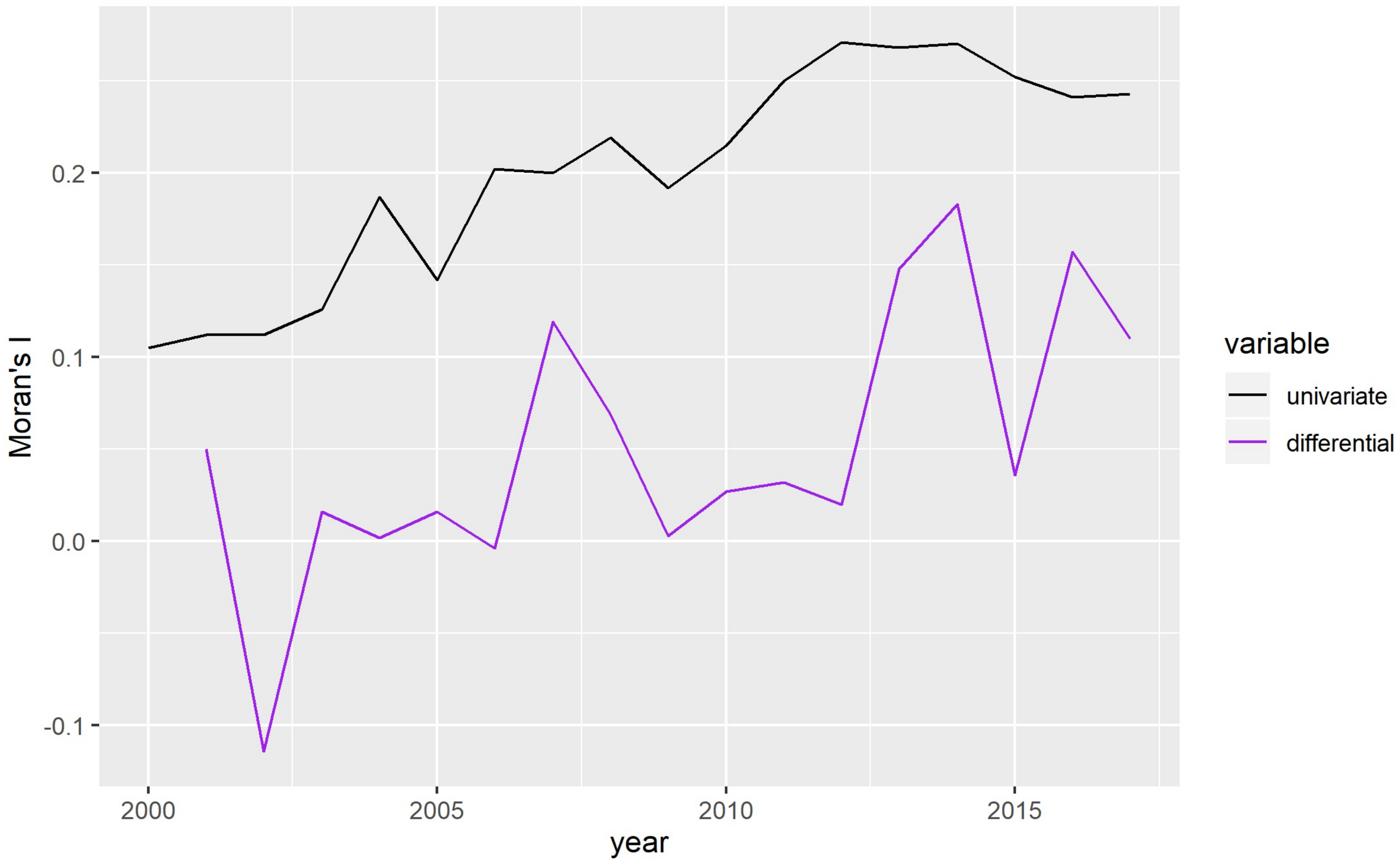
Note : 1. For the beta convergence analysis, the regression include a constant term, which is not presented in the slide.

2. Some missing data in several new districts are interpolated using linear regression

Source : Authors's Calculation

Is spatial dependency at the district level statistically significant?

$$I = \frac{\sum_i \sum_j w_{ij} z_i \cdot z_j}{\sum_i z_i^2} = \frac{\sum_i (z_i \times \sum_j w_{ij} z_j)}{\sum_i z_i^2}.$$



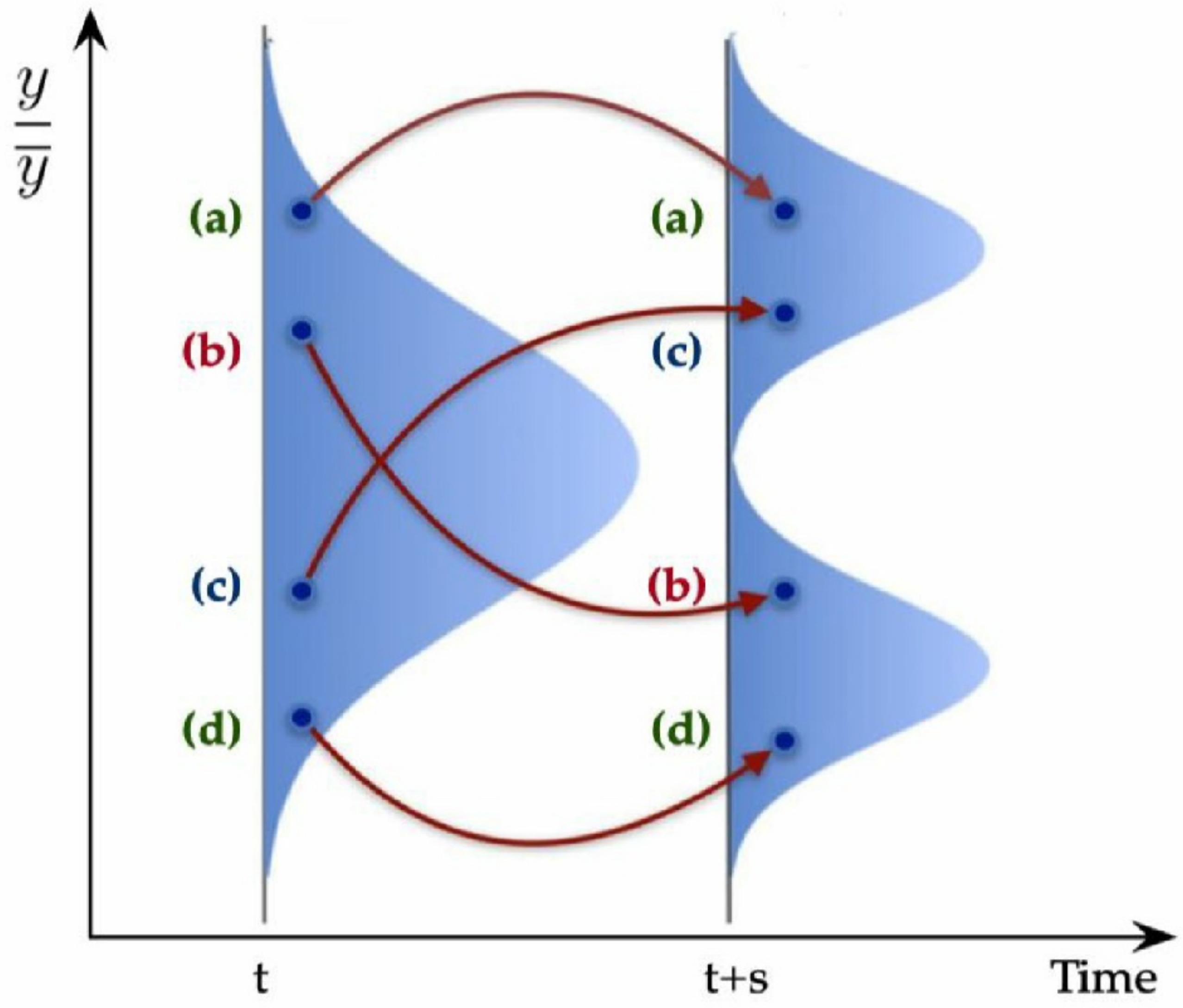
Yes, moreover it is increasing over time.

(2) Distributional convergence

Let's study convergence BEYOND the average

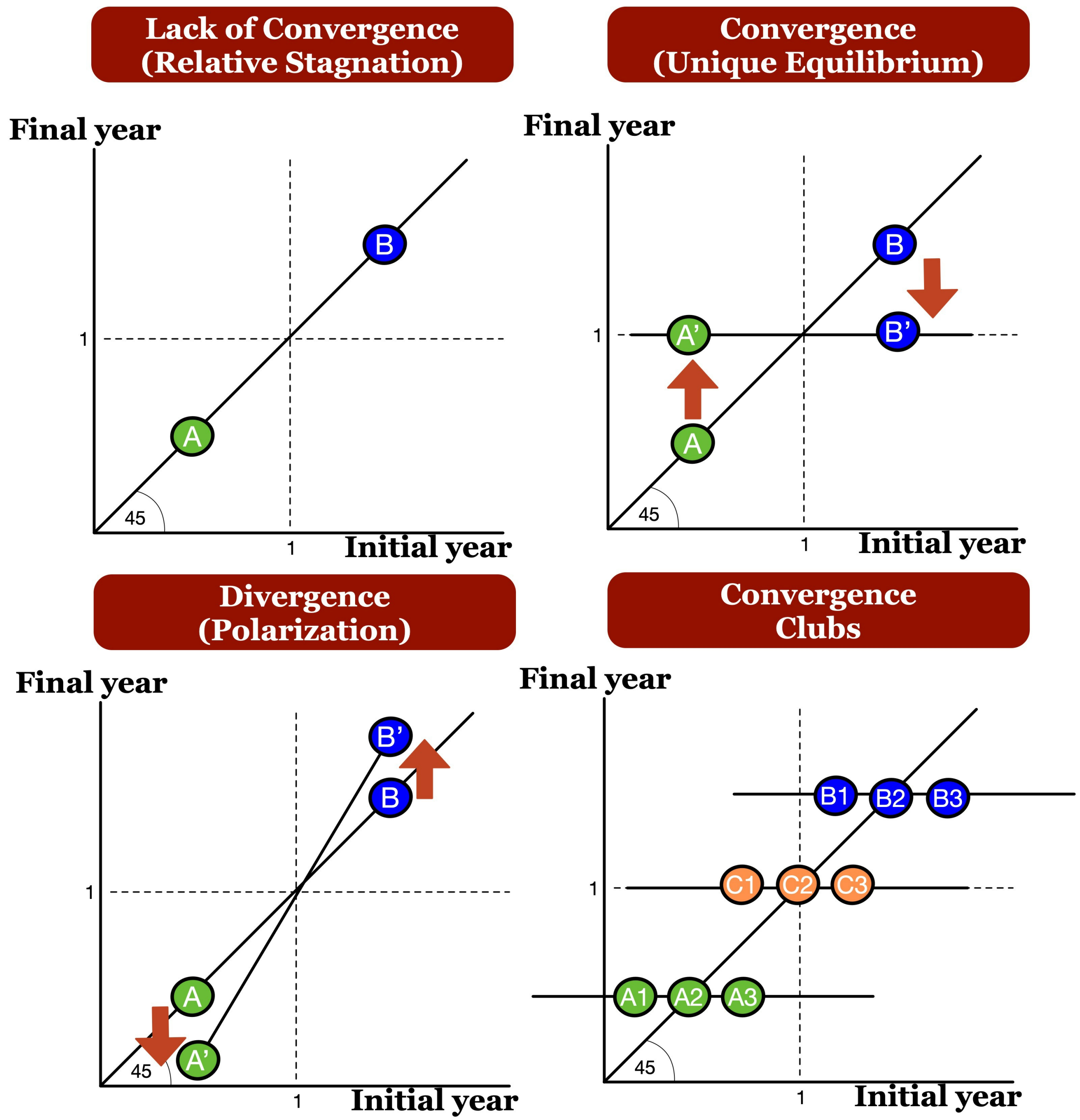
The distribution dynamics framework

$$\underbrace{f_{t+s}(z)}_{Future\ Distribution} = \int \underbrace{f_{t+s|Z_t=x}(z)}_{Transitional\ Operator} \underbrace{f_t(x)}_{Initial\ Distribution} dx$$



Source: Adapted from Quah (1993).

Some illustrative patterns of stagnation, convergence, and divergence



Spatial decomposition framework: The Getis filter

$$x_i^* = \frac{xi(W_i)}{(n-1)G_i(d_m)}$$

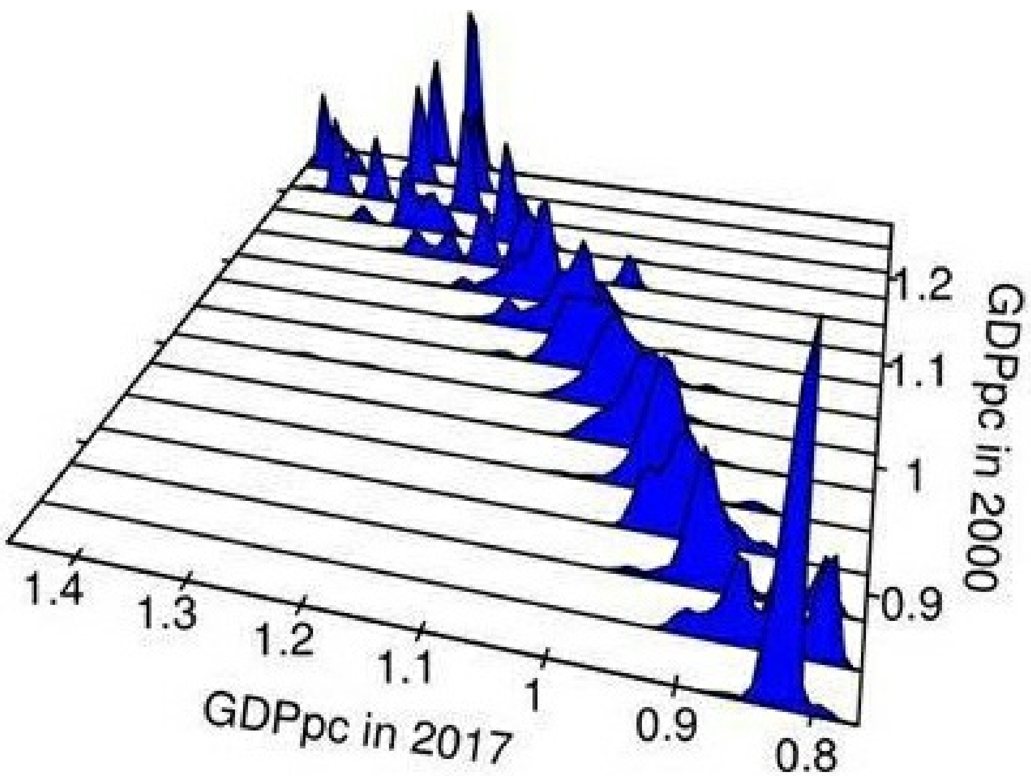
(3) Main Results

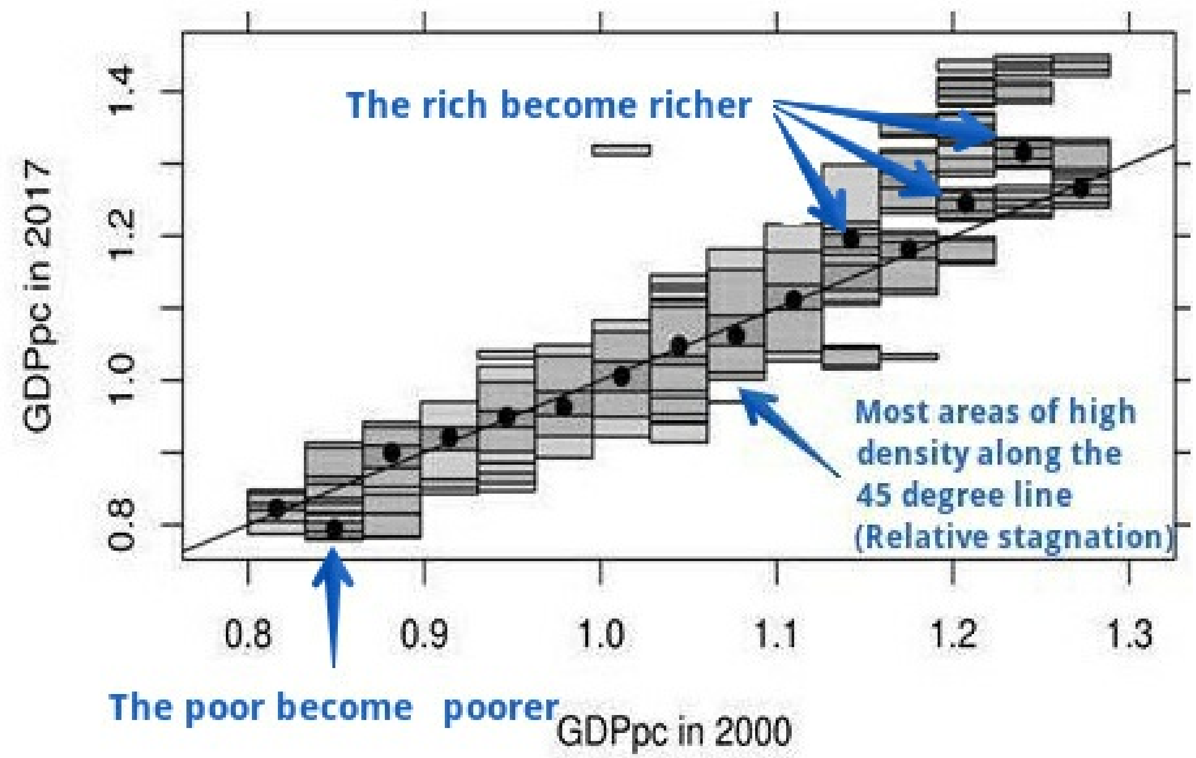
(1) Beyond the average, lack of distributional convergence

(2) Spatial dependece helps reduce extreme disparities

Beyond the average, lack of distributional convergence

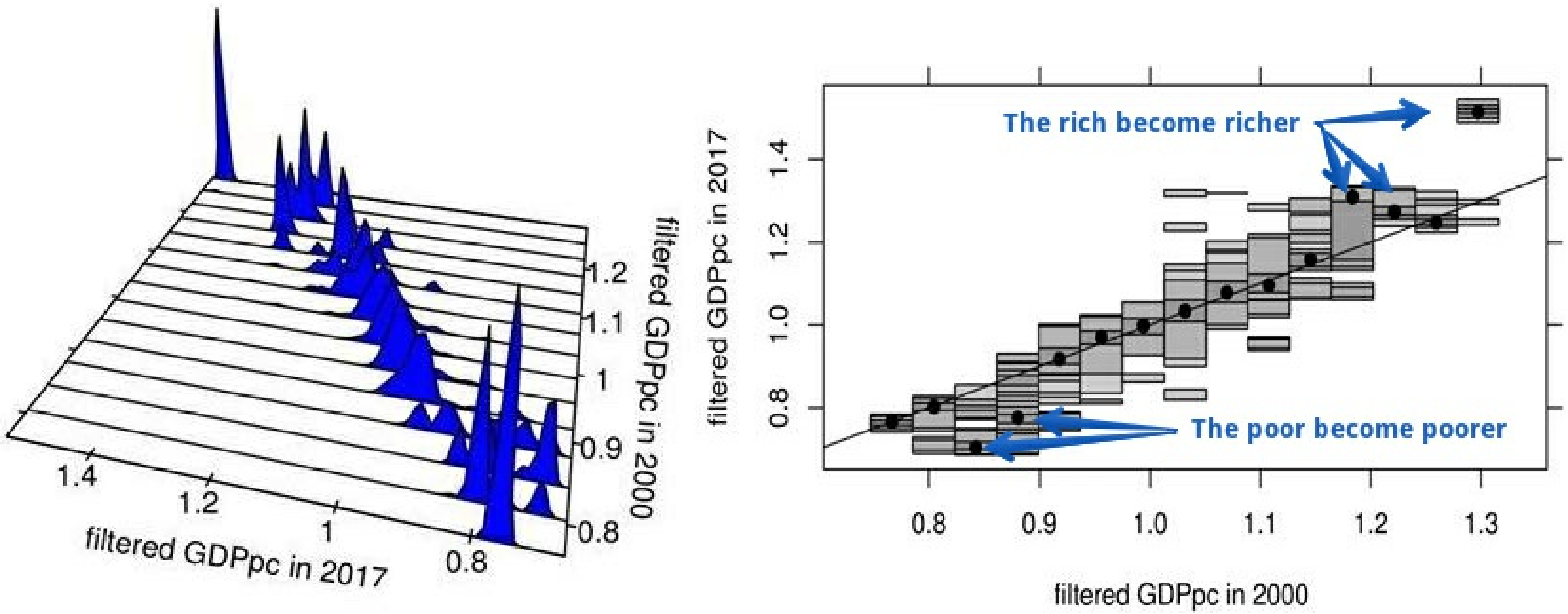
Mostly relative stagnation and divergence at the extremes





Beyond the average, lack of distributional convergence (further polarization)

Distribution dynamics of the non-spatial component



Concluding Remarks

Classical convergence VS Distributional convergence

- Classical: On average, convergence
- Distributional: Beyond the average, lack of convergence

On the role of space

- Increasing spatial autocorrelation
- Geographic neighbors helped reduce some extreme disparities

Implications

- Beyond the average progress, regional inequality is still an issue
- For further research :
    - Using district-level data, what is the role of geographical neighbors in accelerating the speed of convergence?
    - Using the time series of the district-level data, are there convergence clubs?
    - Integration of spatial and dynamic clusters

Thank you very much for your attention

You can find this presentation on our QuaRCS lab website https://quarcs-lab.rbind.io

QuaRCS lab

Quantitative Regional and Computational Science Lab