Regional Inequality and Spatial Structural Change in Chinese cities: A Remote Sensing Approach “Day and Night”

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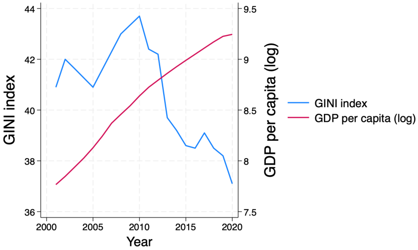
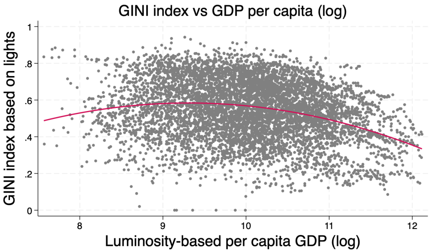
Summary: Three items I did in this paper-I

- Kuznets curve in China: From national[1] to **regional**...



(a) GINI and GDP per capita time series in China



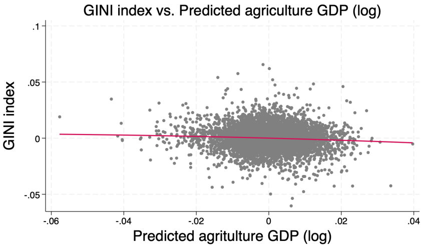
(b) City-level GINI and income (2001-2020)

`Kuznets hypothesis`: Inequality initially increases and subsequently decreases during the course of economic growth (Kuznets, 1955).

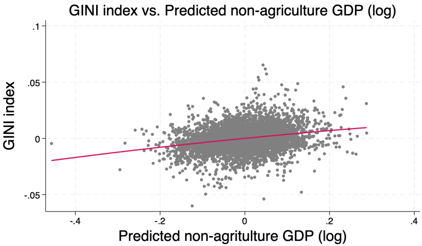
[1] Data source is the World Bank. The GINI is based on the primary household survey. GDP is in constant 2015 US dollars.

Summary: Three items I did in this paper-II

- Kuznets curve in China: From total to **sectoral**...



(a) GINI and agriculture GDP (2001-2020)



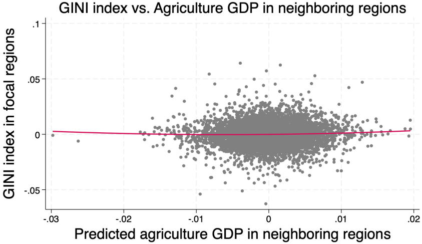
(b) GINI and non-agriculture GDP (2001-2020)

`Kuznets-Lewis theory`:

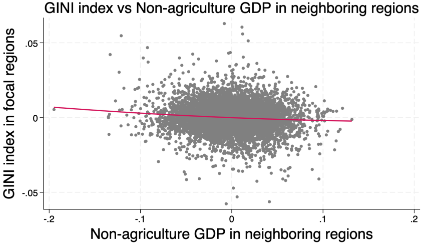
- Inequality increases from the pre-industrial to the industrial period and decreases in the post-industrial period (Lewis et al., 1954; Tribble Jr, 1996).
- Development or resurgence in the agriculture sector help balance the economy (Andersson and Palacio, 2017).

Summary: Three items I did in this paper-III

- Kuznets Curve in China: From independent to **spatially dependent**...



(a) GINI and neighboring agriculture GDP



(b) GINI and neighboring non-agriculture GDP

`New Economic Geography (Krugman, 1991)`: Inequality in focal regions tends to decrease as neighboring areas develop their non-agricultural sectors.

Overview

Objectives

• Explain the dynamics of regional inequality by revisiting the sectoral Kuznets framework;
• Analyze the impact of sectoral economic development on income inequality within Chinese cities, accounting for spatial spillover effects from neighboring regions.

Data

We cover 332 cities in China 2001-2020, including:
• Global NPP-VIIRS-like nighttime light (NTL);
• MODIS MDC12Q1 landcover classfication;
• MODIS MOD17A3HGF net primary productivity (NPP);
• LandScan Population Data;
• Luminosity-based inequality measurement and per capita GDP (Chen, 2024);
• Official city-level sectoral GDP.

Methods

• Remote sensing;
• Within estimator regression models;
• Spatial econometric models.

Originality

• Constructing unique dataset that captures sectoral information for 332 Chinese cities (2001-2020);
• Improving limitations of NTL alone for predicting agricultural output by augmenting day-time landcover and NPP;
• Including the role of space into the sectoral Kuznets framework.

Motivation and background

The critiques confronted by the original Kuznets Lewis hypothesis

- Why *regional*?
  - **Local Factors:** Diverse local influences on inequality and development help reduce omitted variable bias (Shahbaz et al., 2013; Mosconi et al., 2020).
  - **Varied Effects:** Determinants like education can impact inequality differently at national versus provincial levels (Cheng and Wu, 2017).
- Why *sectoral*?
  - **Impact of Structural Change** : Structural changes affect inequality turning points (Gradín et al., 2021; Molero-Simarro, 2017).
  - **Challenging Conventional Belief:** Ravallion and Chen (2022) argues that structural transformation-driven growth does not inevitably increase inequality and cause the turning point.
- Why *spatial*?
  - **New Economic Geography:** The spatial concentration or dispersion of economic activities, and spatial spillovers capture technology diffusion (Krugman, 1991; Ertur and Le Gallo, 2009).
  - **Empirical Evidence:** The shape of Kuznets Curve in China is sensitive to spatial features (Chang et al., 2021). Spatial econometrics help control for the cross-sectional dependence.

Challenges of conducting regional sectoral-specific study in China

Limited data for sectoral characteristics

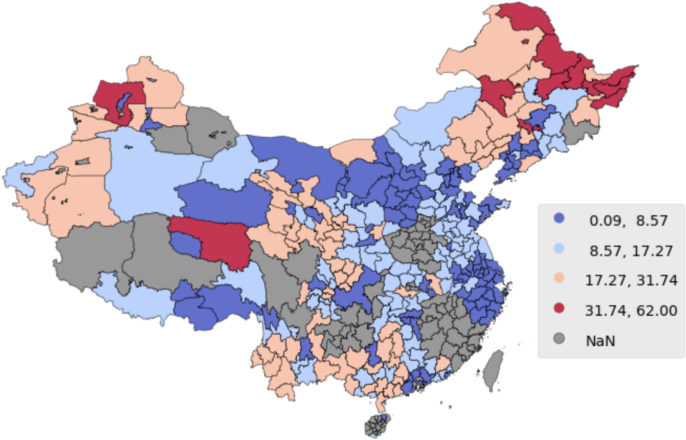
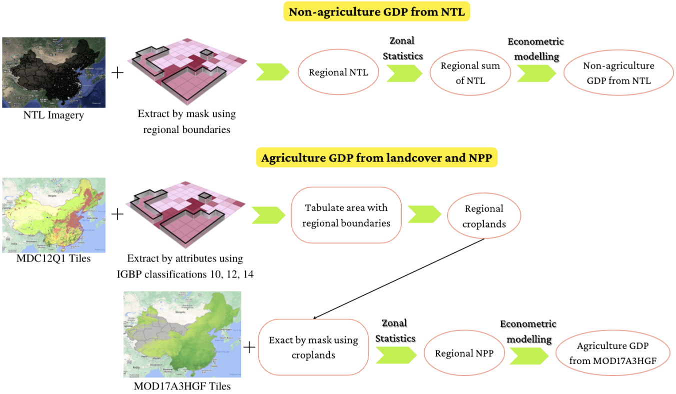


Figure: Spatial distribution for the ratio of agriculture output across Chinese cities in 2020

Solution: Predicting sectoral output

Using the data from satellite imagery[2]



- Nighttime light (NTL) is a poor proxy for agriculture GDP (Chen and Nordhaus, 2019).
- Augmenting croplands with net primary productivity (NPP) could improve the prediction of agricultural output (Pagaduan, 2022).

[2] Access the GEE APP by clicking here.

Research Questions & Objectives

1. **Q1**: How does the development of different economic sectors influence income inequality?
   Obj. 1: To explain the dynamics of regional inequality by revisiting the sectoral Kuznets framework.
   Method: `Remote sensing` & `Two-way fixed effect model`.

2. **Q2**: What is the role of space over the evolution of inequality dynamics and structural change?
   Obj. 2: To analyze how the development of different economic sectors influences income inequality within Chinese cities, considering the effects of neighboring regions.
   Method: `Spatial Econometric model`.

Key literature

Lessmann and Seidel (2017)	**Obj.**: Create and analyze regional income inequality data using NTL. **Data**: DMSP NTL, observed GDP in 82 countries (1503 regions). **Meth.**: Fixed and random effects model.
Pagaduan (2022)	**Obj.**: Improve subnational GDP estimation using satellite data, especially for rural areas. **Data**: VIIRS-like NTL, MOD17A3HGF NPP and MDC12Q1 landcover, 2001-2018. **Meth.**: Within estimator regression.
Chang et al. (2021)	**Obj.**: Revist the environmental Kuznets curve in China considering the spatial spillover effects. **Data**: CO2 emission and GDP data at city level. **Meth.**: Spatial dynamic panel model.

Econometric specification

The limitation of non-spatial two-way fixed effect model:

It neglects exogenous spatially autocorrelated variables that capture spatial externalities in technological or labor markets between regions. This omission could introduce bias to the estimates.

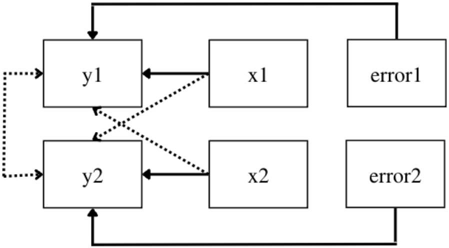


Figure: Diagram of a Spatial Durbin Model (SDM)

Note: 1 and 2 Represent Neighboring Regions.

Econometric specification

Direct and Indirect effect

- Two-way fixed effect model:

$$Gini_{it} = \beta_0 + \beta * X_{it} + \delta_0 d_t + a_i + u_{it} \tag{1}$$

- Spatial Durbin Model (SDM) (LeSage and Pace, 2009):

$$Gini_{it} = \beta_0 + \rho * WGini_{it} + \beta * X_{it} + \theta * WX_{it} + \delta_0 d_t + a_i + u_{it} \tag{2}$$

$$Gini_{i,t} = (I_N - \rho W)^{-1}(\beta * X_{N,t} + \theta * WX_{N,t}) + d + a + u + \beta_0 \tag{3}$$

- The matrix of marginal effect:

$$\left[\frac{\delta E(Gini_t)}{\delta X_{1k,t}} \cdots \frac{\delta E(Gini_t)}{\delta X_{Nk,t}}\right]_t = (I_N - \rho W)^{-1}(I_N \beta_k + W\theta_k) \tag{4}$$

  - **Direct effect**: Average of the diagonal components;
  - **Indirect effect**: Average of the row sums or column sums of the non-diagonal elements.

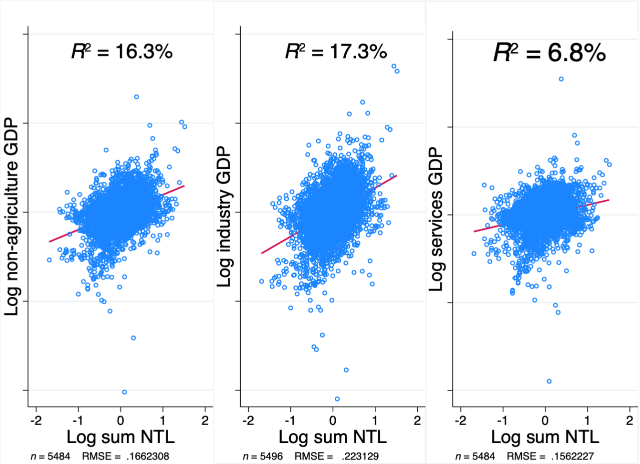
Data

Variable	Source
Dependent variable	
Luminosity-based GINI index	The GINI based on the global NPP-VIIRS-like NTL constructed by Chen (2024)
Independent variable	
Remote sensing variables	
Nighttime light	Global NPP-VIIRS-like nighttime light
Daytime landcover classification	MCD12Q1.061 MODIS Land Cover Type Yearly Global 500m
Daytime net primary productivity	MOD17A3HGF.061: Terra Net Primary Production Gap-Filled Yearly Global 500m
Population	LandScan Population Data
Traditional economic indicators	
Per capita GDP	China City Statistical Year Book
Agricultural GDP	China City Statistical Year Book
Non-agricultural GDP	China City Statistical Year Book

*You can access the data website by clicking the Source.

Predict non-agriculture GDP

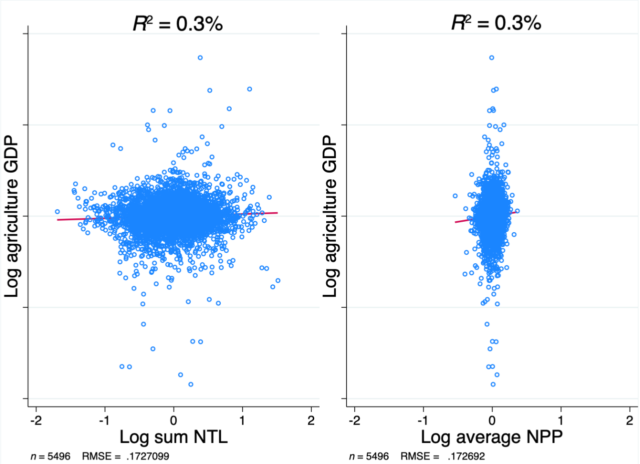
NTL explains a larger proportion of GDP for the non-agriculture sector...



Industrial sector exhibits the highest elasticity between GDP and NTL. Economic activities within the industrial sector are captured most effectively by the NTL satellite sensor (Pagaduan, 2022).

Predict agriculture GDP

Higher elasticity of NPP with agriculture GDP than NTL[3]...



[3] See the regression table of validation for sectoral GDP in Appendix 1.

Kuznets curve: Non-spatial

There is an inverted U shape...

	Regional Inequality (GINI index)			
	(1)	(2)	(3)	(4)
Predicted per capita GDP (log)	0.017***	0.078***	0.072***	-0.007
	(0.005)	(0.013)	(0.014)	(0.025)
Square of predicted per capita GDP (log)		-0.003***	-0.003***	0.000
		(0.001)	(0.001)	(0.001)
Ratio Of non-agriculture GDP (%) (predicted)				0.156***
				(0.038)
Urbanisation			-0.025	-0.023
			(0.016)	(0.016)
Constant	0.020	-0.269***	-0.236***	0.108
	(0.042)	(0.073)	(0.076)	(0.119)
Observations	6,640	6,640	6,640	6,640
R-squared	0.029	0.067	0.071	0.102
Number of city	332	332	332	332
Regional Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Turning points	-	12.162	12.508	-

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure: Non-spatial Kuznets curve controlling for region and year fixed effects (2001-2020)

...inequality initially increases and decreases as the income level increases in Chinese cities (Ravallion and Chen, 2022; Lin and Brueckner, 2024).

Sectoral Kuznets curve: Non-spatial

Only the non-agriculture sector presents the inverted-U shape...

	Regional Inequality (GINI index)					
	(1)	(2)	(3)	(4)	(5)	(6)
Predicted agriculture GDP (log)	-0.082**	-0.084**			-0.085***	
	(0.034)	(0.034)			(0.033)	
Square of predicted agriculture GDP (log)		0.000			0.000	
		(0.001)			(0.001)	
Predicted non-agriculture GDP (log)			0.029***	0.039***		0.037***
			(0.004)	(0.006)		(0.006)
Square of predicted non-agricultural GDP (log)				-0.001***		-0.001***
				(0.000)		(0.000)
Urbanisation					-0.049***	-0.034**
					(0.017)	(0.016)
Constant	0.485***	0.488***	0.021	-0.001	0.503***	0.013
	(0.127)	(0.126)	(0.023)	(0.024)	(0.124)	(0.025)
Observations	6,640	6,640	6,640	6,640	6,640	6,640
R-squared	0.018	0.018	0.062	0.080	0.032	0.086
Number of city	332	332	332	332	332	332
Regional Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Turning points	-	-	-	19.984	-	21.186

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure: Fixed-effects regression of spatial income inequality on GDP by sector

...while agricultural production is mainly negatively associated with disparities (Cheng and Wu, 2017).

Kuznets curve: Spatial

A robust inverted U shape with earlier turning points...

	(1)	(2)
Direct Effects		
Predicted per capita GDP (log)	0.078***	0.074***
	(0.004)	(0.004)
Square of per capita GDP (predicted)	-0.003***	-0.003***
	(0.000)	(0.000)
Urbanisation		-0.020***
		(0.005)
Indirect Effects		
Predicted per capita GDP (log)	0.009	-0.007
	(0.008)	(0.009)
Square of per capita GDP (predicted)	-0.001***	-0.000
	(0.000)	(0.000)
Urbanisation		-0.072***
		(0.012)
Total Effects		
Predicted per capita GDP (log)	0.088***	0.067***
	(0.008)	(0.009)
Square of per capita GDP (predicted)	-0.004***	-0.003***
	(0.000)	(0.000)
Urbanisation		-0.091***
		(0.013)
Observations	6640	6640
Number of cities	332	332
R-squared	0.04	0.06
City Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Turning point	11	11.17

Notes: The dependent variable is the GINI index in each city.
All models include a constant
$*p < 0.10, **p < 0.05, ***p < 0.01$

...there is no significant effect from the neighboring cities.

Sectoral Kuznets curve: Spatial

Non-agriculture: Early turning points, reverse patterns for focal and neighboring regions...

	(1)	(2)
Direct Effects		
Predicted agriculture GDP (log)	-0.102***	
	(0.017)	
Square of predicted agriculture GDP (log)	0.000**	
	(0.000)	
Predicted non-agriculture GDP (log)		0.043***
		(0.002)
Square of predicted non-agriculture GDP (log)		-0.001***
		(0.000)
Urbanisation	-0.043***	-0.028***
	(0.005)	(0.005)
Indirect Effects		
Predicted agriculture GDP (log)	0.046	
	(0.031)	
Square of predicted agriculture GDP (log)	0.000	
	(0.000)	
Predicted non-agriculture GDP (log)		-0.021***
		(0.004)
Square of predicted non-agriculture GDP (log)		0.000**
		(0.000)
Urbanisation	-0.080***	-0.076***
	(0.012)	(0.012)
Total Effects		
Predicted agriculture GDP (log)	-0.056**	
	(0.027)	
Square of predicted agriculture GDP (log)	0.001	
	(0.000)	
Predicted non-agriculture GDP (log)		0.022***
		(0.003)
Square of predicted non-agriculture GDP (log)		-0.001***
		(0.000)
Urbanisation	-0.122***	-0.103***
	(0.013)	(0.013)
Observations	6640	6640
Number of cities	332	332
R-squared	0.0016	0.014
City Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Turning point	-	11

Notes: The dependent variable is the GINI index in each city.
All models include a constant
$*p < 0.10, **p < 0.05, ***p < 0.01$

...agricultural development negatively correlates with disparities, with no significant spatial effects.

Conclusion

- **Use of remote sensing:** The combination of night-time and day-time satellite data could be a viable and cost-effective alternative for tracking regional sectoral development in China over time, in addition to traditional censuses and statistics;
- **A sectoral perspective**: The non-agriculture sector presents the similar inverted U pattern to the original Kuznets hypothesis. The inequality initially increases and then decreases with the development in the overall income and non-agricultural sector.
- **A spatial perspective:**
  - Spatial effects are significant for regional inequality and structural change.
  - For the non-agriculture sector, the direct impact of non-agriculture in focal regions follows an inverted U-shaped relationship with inequality, whereas the indirect effect of output from neighboring regions exhibits a U-shaped relationship with inequality.
  - Agricultural development, on the other hand, is negatively associated with inequality both before and after considering spatial effects.
  - After incorporating the spatial effects, the turning points occurred at earlier stages.
- **Policy implication:** Achieving regional balance could be facilitated by both a resurgence in the agricultural sector and the enhancement of spatial connectivity in the non-agricultural sector.

Limitations and further study

- **Sectoral GDP captures part of the picture**: Sectoral GDP primarily reflects changes in the output (production) of each sector. While valuable, it doesn't capture the entire picture of structural transformation.
- **Regional heterogeneity**: Despite considering the spatial spillover effects, spatial econometrics is still based on the average level. However, the inequality-income relationship may vary across different regions throughout China. Considering the spatial heterogeneity would be essential in further study (using MGWR in the next chapter).


ຂອບໃຈ
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Cảm ơn
សូមអរគុណ
¡Muchas GRACIAS!
شكرًا
ご清聴ありがとうございました
MERCI BEAUCOUP!
Thank you
Terima kasih
谢谢观看

Appendix 1: Validation test: Non-agriculture and agriculture sectors

	(1) Log (total GDP)	(2) Log (non-agriculture)	(3) Log (industry)	(4) Log (services)	(5) Log (agriculture)
Log total sum of lights	0.160***	0.193***	0.269***	0.106***	0.031*
	(0.013)	(0.016)	(0.021)	(0.016)	(0.017)
Constant	4.147***	3.679***	2.392***	3.616***	3.521***
	(0.103)	(0.130)	(0.173)	(0.125)	(0.127)
Observations	6,530	5,544	5,556	5,544	5,556
R-squared	0.935	0.926	0.865	0.940	0.801
Number of city_id	332	325	325	325	325
Regional FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(a) Fixed effects regression of total and sectoral GDP on NTL at city level

	Log (agriculture GDP) (1)	(2)
Log (croplands)	-0.137	
	(0.084)	
Log average NPP (net primary productivity) in the rural area		0.104*
		(0.062)
Constant	4.897***	3.155***
	(0.697)	(0.368)
Observations	5,556	5,556
R-squared	0.802	0.801
Number of city_id	325	325
Regional FE	Yes	Yes
Year FE	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

(b) Fixed effects regression of agriculture GDP on cropland area and net primary productivity (NPP) at city level

Appendix 2: Model specification and regression results

	(1)	(2)
Main explanatory variables		
Predicted per capita GDP (log)	0.078***	0.074***
	(0.004)	(0.004)
Square of per capita GDP (predicted)	-0.003***	-0.003***
	(0.000)	(0.000)
Urbanisation		-0.019***
		(0.005)
Spatial lags of the explanatory variables		
Predicted per capita GDP (log)	0.000	-0.012
	(0.008)	(0.008)
Square of per capita GDP (predicted)	-0.001**	-0.000
	(0.000)	(0.000)
Urbanisation		-0.066***
		(0.012)
Spatial lag of dependent variable		
ρ	0.095***	0.081***
	(0.020)	(0.020)
Observations	6640	6640
Number of cities	332	332
R-squared	0.04	0.06
City Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes

Notes: The dependent variable is the GINI index in each city.
All models include a constant
$*p < 0.10, **p < 0.05, ***p < 0.01$

(a) Spatial Kuznets curve

	(1)	(2)
Main explanatory variables		
Predicted agriculture GDP (log)	-0.103***	
	(0.017)	
Square of predicted agriculture GDP (log)	0.000**	
	(0.000)	
Predicted non-agriculture GDP (log)		0.043***
		(0.002)
Square of predicted non-agriculture GDP (log)		-0.001***
		(0.000)
Urbanisation	-0.042***	-0.027***
	(0.005)	(0.005)
Spatial lags of the explanatory variables		
Predicted agriculture GDP (log)	0.053*	
	(0.029)	
Square of predicted agriculture GDP (log)	0.000	
	(0.000)	
Predicted non-agriculture GDP (log)		-0.023***
		(0.003)
Square of predicted non-agriculture GDP (log)		0.000**
		(0.000)
Urbanisation	-0.070***	-0.068***
	(0.011)	(0.011)
Spatial lag of dependent variable		
ρ	0.088***	0.088***
	(0.020)	(0.020)
Observations	6640	6640
Number of cities	332	332
R-squared	0.0016	0.014
City Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variable is the GINI index in each city.
All models include a constant
$*p < 0.10, **p < 0.05, ***p < 0.01$

(b) Spatial Kuznets curve by sector

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