### The Role of Cities

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Economic Geography FGV EPGE

## Cities are key elements of economic geography

- $\triangleright$  1–3% of the available land area, but over half of the population
- ▶ What sustain these high densities? Why do cities exists?
- ▶ What economic role do cities play?
- ▶ Focus: developing economies, where most of the urban growth occurs

# What is different about urbanization in rich and poor countries? Cities in Brazil, China, India and the United States

Chauvin, Glaeser, Ma and Tobio

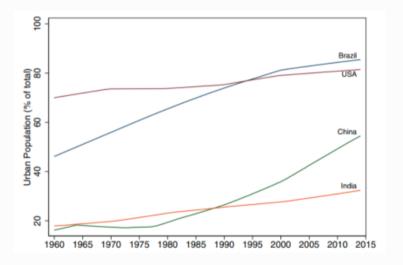
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#### Motivation

- ▶ Big question in development: if results obtained in developed economies may be extended to developing economies
- ▶ What do we know about urbanization in rich economies (mostly the US)?
  - driven by agglomeration economies
  - they also allow human capital externalities
  - ► Gilbrat's law: growth is unrelated to initial size
  - labor mobility lead to a spatial equilibrium: more desirable and productive locations are also more congested and more expensive to live in
- ▶ Do such patterns hold in developing economies?
  - why these countries? Large, varied, no primal city

## Urbanization over time in these four countries



## Challenge: to obtain comparable city definitions

- ▶ The authors decide to stick with census definitions
- US: Metropolitan Statistical Areas
  - do not cover all the country
  - include all inhabitants of the region
- Brazil: microregions
  - include all municipalities
  - include rural residents
- ► China: administrative "cities"
- ► India: districts
- ► As an attempt for harmonization, only units of more than 100,000 inhabs used

# City size distributions

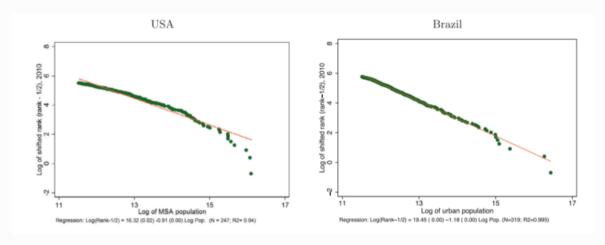
	Areas of 100 K – 250 K (percent)	Areas of 250 K – 500 K (percent)	Areas of 500 K – 1 M (percent)	Areas of 1 M - 1.5 M (percent)	Areas of 1.5 M+ (percent)	Population in areas 100 K+ (millions)
2000						
USA (MSAs)	5%	8%	8%	6%	38%	184
Brazil (Microregions)	17%	12%	9%	5%	30%	123
China (Cities)	0.3%	1.2%	6%	8%	21%	458
India (Districts)	2%	5%	6%	4%	10%	279
2010 (2011 for India)						
USA (MSAs)	5%	7%	9%	5%	41%	207
Brazil (Microregions)	16%	12%	11%	6%	32%	148
China (Cities)	0.2%	0.8%	4%	6%	39%	669
India (Districts)	2%	4%	6%	4%	14%	373

### City size distributions: KS tests

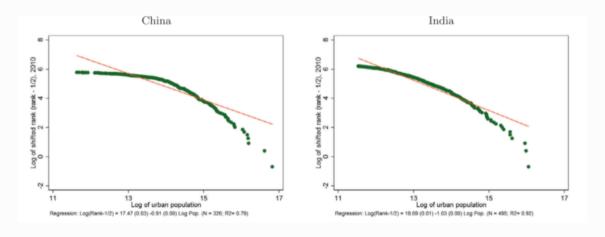
	Brazil (Microregions)	China (Cities)	India (Districts)
Full Sample			
USA (MSAs)	0.396 (0.000)	0.534 (0.000)	0.194 (0.000)
Brazil (Microregions)		0.779 (0.000)	0.346 (0.000)
China (Cities)			0.564 (0.000)
Cities with urban popu	lation of 500,000 or mo	re	
USA (MSAs)	0.148 (0.432)	0.229 (0.001)	0.123 (0.286)
Brazil (Microregions)		0.342 (0.000)	0.085 (0.911)
China (Cities)			0.301 (0.000)

*Note:* Figures are D test-statistic scores, p-values in parentheses. The observations in the full sample are: US = 258, Brazil = 548, China = 345 and India = 632. The observations in the restricted sample are: US = 93, Brazil = 55, China = 296 and India = 204.

## Zipf's law holds well for the USA and Brazil...



#### but not in India or China



# Gibrat's law: log growth versus log initial size

	USA	Brazil	China	India
	(MSAs)	(Microregions)	(Cities)	(Districts)
1980-2010	0.009	-0.038	-0.447***	-0.052**
	(0.020)	(0.023)	(0.053)	(0.023)
	N = 217	N = 144	N = 187	N = 237
	R2 = 0.001	R2 = 0.015	R2 = 0.280	R2 = 0.021
1980-1990	0.008	-0.026**	-0.310***	0.063*
	(0.008)	(0.013)	(0.054)	(0.034)
	N = 217	N = 144	N = 187	N = 237
	R2 = 0.004	R2 = 0.020	R2 = 0.151	R2 = 0.015
1990-2000	0.014**	0.001	-0.308***	0.005
	(0.007)	(0.010)	(0.036)	(0.020)
	N = 217	N = 144	N = 187	N = 237
	R2 = 0.019	R2 = 0.000	R2 = 0.280	R2 = 0.00
2000–2010	0.012**	0.006	0.019	-0.013
	(0.006)	(0.006)	(0.021)	(0.015)
	N = 217	N = 144	N = 187	N = 237
	R2 = 0.018	R2 = 0.006	R2 = 0.005	R2 = 0.004

# Testing spatial equilibria: are higher wage cities more expensive to live in?

	USA	Brazil	China	India	USA	China
	(MSAs)	(Microregions)	(Cities)	(Districts)	(MSAs)	(Cities)
		Log of 1	rents		Log of	prices
Average log wage	1.225***	1.011***	0.853***	-0.044	1.922***	1.122 ***
	(0.106)	(0.044)	(0.157)	(0.052)	(0.172)	(0.073)
	N = 29 M	N = 819 K	N = 6.5 K	N = 1484	N = 56 M	N = 24.5 K
	R2 = 0.208	R2 = 0.560	R2 = 0.187	R2 = 0.304	R2 = 0.396	R2 = 0.521
Average log wage residual	1.612***	1.367***	1.810***	-0.019	2.887***	1.097***
	(0.159)	(0.076)	(0.167)	(0.060)	(0.256)	(0.122)
	N = 29 M	N = 819 K	N = 6.5 K	N = 1484	N = 56 M	N = 24.8 K
	R2 = 0.202	R2 = 0.552	R2 = 0.311	R2 = 0.304	R2 = 0.403	R2 = 0.515
Dwelling characteristics	Yes	Yes	Yes	Yes	Yes	Yes

Note: Regressions at the urban household level, restricted to areas with urban population of 100,000 or more. All regressions include a constant. Standard errors clustered at the area level in parentheses. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

# Testing spatial eq.: temperature and real wages correlate differently in Brazil than in the US

	USA (MSAs)	USA (MSAs)				Brazil (Microregions)		
	Log wage	Log real wage	Log rent	Log price	Log wage	Log real wage	Log rent	
Absolute difference from ideal	0.001	0.006***	-0.027***	-0.066***	-0.084***	-0.045***	-0.110***	
temperature in the summer	(0.003)	(0.002)	(800.0)	(0.015)	(0.007)	(0.003)	(0.016)	
Absolute difference from ideal	0.002	0.005***	-0.018***	-0.032***	-0.015**	-0.005	-0.012	
temperature in the winter	(0.002)	(0.001)	(0.003)	(0.007)	(0.006)	(0.004)	(0.010)	
Average annual rainfall	-0.006	0.005	-0.054**	-0.129***	0.063***	0.010	0.179***	
(std. deviations from the mean)	(0.008)	(0.007)	(0.026)	(0.033)	(0.015)	(0.009)	(0.028)	
Education groups controls	Y	Y	N	N	Y	Y	N	
Age groups controls	Y	Y	N	N	Y	Y	N	
Dwelling characteristics controls	N	N	Y	Y	N	N	Y	
Observations (thousands)	28,237	8497	24,125	44,765	2157	2157	2157	
Adjusted R-squared	0.249	0.158	0.117	0.372	0.341	0.315	0.477	

# Testing spatial eq.: and no correlation in China or India

	China (Cities)				India (Districts)		
	Log wage	Log real wage	Log rent	Log price	Log wage	Log real wage	Log rent
Absolute difference from ideal	-0.005	-0.006	-0.001	0.000	0.000	-0.004	0.001
temperature in the summer	(0.018)	(0.015)	(0.021)	(0.037)	(0.004)	(0.006)	(0.001)
Absolute difference from ideal	0.003	-0.004	0.019**	0.035*	-0.001	0.003	0.000
temperature in the winter	(0.009)	(0.009)	(0.009)	(0.018)	(0.003)	(0.004)	(0.001)
Average annual rainfall	0.109	0.021	0.256***	0.164	0.063**	0.049*	-0.005
(std. deviations from the mean)	(0.067)	(0.055)	(0.069)	(0.142)	(0.025)	(0.036)	(0.013)
Education groups controls	Y	Y	N	N	Y	Y	N
Age groups controls	Y	Y	N	N	Y	Y	N
Dwelling characteristics controls	N	N	Y	Y	N	N	Y
Observations (thousands)	5.8	4.2	3.4	6.1	8.4	1.8	2.9
Adjusted R-squared	0.145	0.118	0.079	0.070	0.235	0.228	0.762

## What about agglomeration economies?

- ► Fact to be documented: does a larger city size increase wages (labor productivity)?
- ► Hard identification problem as city size depends on geographic fundamentals **and** as more productive people self-select into cities
- ► The paper uses historic city sizes (in 1980 or 1900) as an IV
- ▶ IV does not resolve sorting, and the paper controls for labor force characteristics
- ► Still, results should be interpreted with caution

# Agglomeration economies seem strong (but noisy) for developing countries

	USA (MSAs) Log wage	Brazil (Microregions) Log wage	China (Cities) Log wage	India (Districts) Log wage
OLS regressions				
Log of urban population	0.0538*** (0.00720) R2 = 0.255	0.052*** (0.013) R2 = 0.321	0.0875 $(0.0708)$ $R2 = 0.014$	$0.0770^{***}$ (0.0264) R2 = 0.251
Log of density	$0.0457^{***}$ (0.00865) R2 = 0.235	0.026** (0.010) R2 = 0.318	0.192*** (0.0321) R2 = 0.237	$0.0760^{***}$ (0.0195) R2 = 0.257
Observations	28.5 M	2172 K	147 K	9778
IV1 regressions				
Log of urban population	$0.0559^{***}$ (0.00753) R2 = 0.256	0.051*** (0.014) R2 = 0.321	0.0320 $(0.102)$ $R2 = 0.173$	0.160 $(0.0998)$ $R2 = 0.237$
Log of density	$0.0431^{***}$ (0.00888) R2 = 0.253	0.026** (0.011) R2 = 0.318	0.169*** (0.0367) R2 = 0.240	$0.0828^{***}$ (0.0218) R2 = 0.253
Observations	28.5 M	2172 K	143 K	7627
IV2 regressions				
Log of urban population	0.0764*** (0.0130) R2 = 0.255 0.0493*** (0.0173)	0.015 (0.021) R2 = 0.315 0.015 (0.012)	0.320* (0.156) R2 = 0.117 0.323*** (0.0847)	0.233** (0.0963) R2 = 0.224 0.0749*** (0.0229)
	R2 = 0.253	R2 = 0.315	R2 = 0.242	R2 = 0.256
Observations	28.5 M	1998 K	112 K	5245
Educational attainment controls Demographic controls	Yes Yes	Yes Yes	Yes Yes	Yes Yes

Note: Regressions at the individual level, restricted to urban prime-age males in areas with urban population of 100,000 or more. All regressions include a constant. Standard errors clustered at the area level in parentheses. ""p < 0.01, "p < 0.05," p < 0.1.

# Probably not driven by sorting if real wages are unrelated with city size (in a spatial eq.)

	USA (MSAs) Log real wage	Brazil (Microregions) Log real wage	China (Cities) Log real wage	India (Districts Log real wage
OLS regressions				
Log of urban population	0.0190** (0.00916) R2 = 0.067	0.011 (0.010) R2 = 0.310	-0.0313 (0.0307) R = 0.174	0.0688** (0.0298) R2 = 0.240
Log of density	0.0219 (0.0134) R2 = 0.068	0.002 (0.007) R2 = 0.309	0.0516** (0.0166) R2 = 0.179	$0.0691^{***}$ (0.0213) R2 = 0.244
Observations	28.5 M	2172 K	147 K	2102
IV1 regressions				
Log of urban population	0.0209** (0.0102) R2 = 0.068	0.009 (0.010) R2 = 0.310	-0.0664 (0.0485) R2 = 0.174	0.116 $(0.0927)$ $R2 = 0.243$
Log of density	0.0230* (0.0134) R2 = 0.068	0.001 $(0.007)$ $R2 = 0.309$	$0.0345^*$ (0.0175) R2 = 0.179	$0.0647^{**}$ (0.0255) R2 = 0.241
Observations	28.5 M	2172 K	143 K	1649
IV2 regressions				
Log of urban population	0.0466** (0.0190) R2 = 0.065	-0.017 (0.016) R2 = 0.305	0.0648 (0.0743) R2 = 0.161	0.208** (0.0840) R2 = 0.244
Log of density	0.0419** (0.0163) R2 = 0.067	-0.008 (0.008) R2 = 0.307	0.0665 (0.0625) R2 = 0.179	0.0512* $(0.0263)$ $R2 = 0.241$
Observations	28.5 M	1998 K	112 K	1141
Educational attainment controls Demographic controls	Yes Yes	Yes Yes	Yes Yes	Yes Yes

Note: Regressions at the individual level, restricted to urban prime-age males in areas with urban population of 100,000 or more. All regressions include a constant. Standard errors clustered at the area level in parentheses. \*\*\* p<0.01, \*\*\* p<0.05. \*\*\* p<0.01.

## What about human capital externalities?

- ► Fact to be documented: does a more educated labor force increase wages (labor productivity)?
- ► Two IV approaches:
  - historic (1980) education levels
  - uses demographic composition in 1980 to predict it for 2010 and then average education by demographic group

## Human capital externalities seem quite large for developing countries

	USA (MSAs)	SA (MSAs)		oregions)	China (Cities	)	India (Distric	cts)
	Log wage	Log wage	Log wage	Log wage	Log wage	Log wage	Log wage	Log wage
OLS regressions								
Share of Adult population with BA	1.272***	1.001***	3.616***	4.719***	6.743***	5.262***	3.215***	1.938**
	(0.155)	(0.200)	(0.269)	(0.440)	(1.088)	(0.862)	(0.851)	(0.841)
Log of density		0.0241***		-0.029***		0.112***		0.0542***
		(0.00746)		(0.008)		(0.0199)		(0.0169)
R-squared	0.26	0.255	0.342	0.346	0.120	0.139	0.256	0.255
Observations (thousands)	34 M	27 M	2172 K	21,712 K	147 K	147 K	12 K	12 K
IV1 regressions								
Share of Adult population with BA	1.237***	1.126***	2.985***	3.784***	6.572***		2.911***	2.124**
	(0.202)	(0.231)	(0.332)	(0.486)	(0.925)		(0.988)	(1.074)
Log of density		0.0216***		-0.018**				0.0425**
-		(0.00769)		(0.009)				(0.0178)
R-squared	0.254	0.255	0.341	0.344	0.120		0.240	0.243
Observations	27 M	27 M	2172 K	2172 K	147 K		11 K	11 K
IV2 regressions								
Share of Adult population with BA	1.594***	0.956**	4.166***	6.705***	7.189***		8.126**	7.989
	(0.380)	(0.396)	(1.059)	(1.756)	(1.437)		(3.458)	(5.521)
Log of density		0.00654		-0.052**				-0.0107
-		(0.0155)		(0.023)				(0.0615)
R-squared	0.228	0.232	0.341	0.341	0.120		0.206	0.212
Observations (thousands)	17 M	16 M	2172 K	2172 K	147 K		10 K	10 K
Educational attainment controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Age controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Regressions at the individual level, restricted to urban prime-age males in areas with urban population of 100,000 or more. All regressions include a constant. Standard errors clustered at the area level in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

# Breaking into tradables: Urban form and urban function in a developing city

Venables

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## Two types of theories about cities

- 1. System of cities models
  - ► Henderson (1974), Duranton and Puga (2013)
  - cities have a type: the tradable industry they are based on
  - congestion forces (land is scarce) × agglomeration forces (localization/Marshall economies)
  - benchmark model ignores space

#### 2. Central place theory

- Lösch (1934), Hsu (2012)
- cities have a non-tradable function serving a rural
- agglomeration economies imply cities at only a few locations
- cast agglomeration shadows
- models must include space

This paper: abstracts from space, but includes both functions

#### Model

- Single city
- ► Labor is the only factor of production (land is used to house workers)
- ▶ Tradable (*T*) and non-tradabale (*N*) sectors:  $L = L_T + L_N$
- Non-tradable prod. function:  $L_N \to Y_N$ , so  $p_N = w$
- ightharpoonup T is the numerarire, and its productivity  $a(L_Y)$  may be increasing in employment
- ▶ Upward sloped (inverse) labor supply:  $w^{S}(L)$

## Non-tradable sector equilibrium

► Equilibrium in *N* market is given by

$$wL_N = (1 - \theta)wL + wh(w)$$

where h(.) is the hinterland demand for N and  $\theta$  the expenditure share of N

 $\blacktriangleright$  Hence, wages are positively related to  $L_T$ :

$$w = h^{-1}(\theta L - L_T)$$

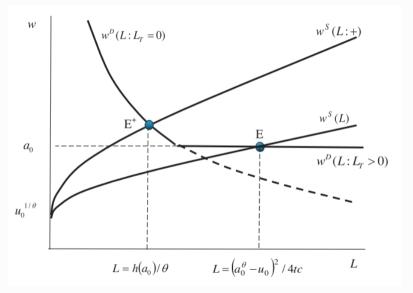
# Deriving labor demand

► Two cases:

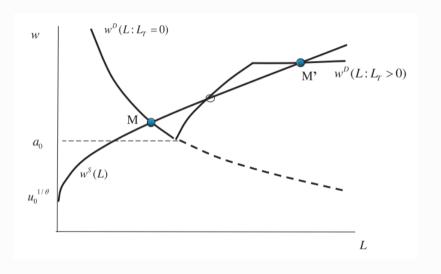
- 1. No *T* sector  $(L_T = 0)$ :  $w^D(L|L_T = 0) = h^{-1}(\theta L)$
- 2. T sector  $(L_T > 0)$ :  $w^D(L|L_T > 0) = a(L_T^*)$  where  $a(L_T^*) = h^{-1}(\theta L L_T^*)$
- ▶ So there is no entry or exit of *T* firms, we have that:

$$w^{D}(L) = max \left\{ h^{-1}(\theta L), \quad a(L_{T}^{*}) \right\}$$

# Equilibrium with CRS



# Equilibrium with agglomeration economies



# Has climate change driven urbanization in Africa?

Henderson, Storeygard, Deichmann

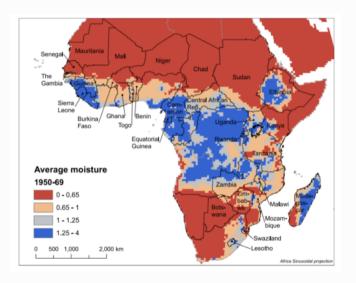
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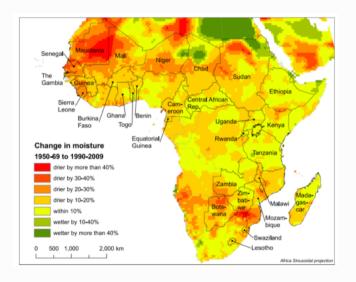
#### Motivation

- ► Long-run macro effects of climate change?
- ► Climate change may force people to move: environmental refugees
- ► Africa has dried up, particularly at the Sahel
- ▶ Did such climate change caused urbanization?
- Yes, but it depends on city function!

## Average moisture in Africa by independence...

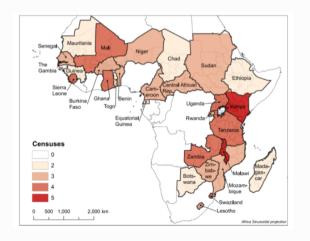


#### ...has decreased over time



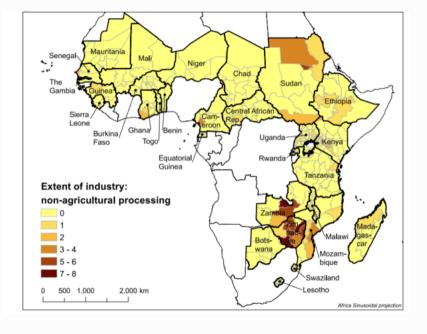
#### Data

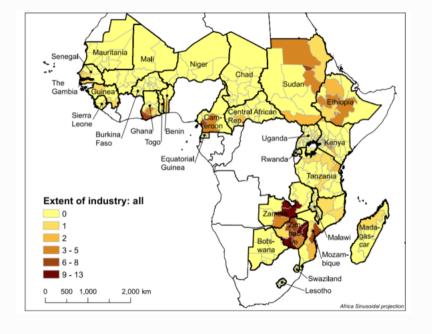
- ▶ Data on population at subnational levels from different censuses
  - ▶ since 1960, up to 2010
  - ▶ 29 countries



#### Data

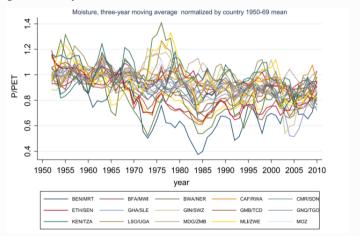
- Data on industries by city
  - ► Oxford Regional Economic Atlas, Africa (1965)
  - ► 26 manufacturing industries
  - ▶ 16 modern sectors (non-ag processing): iron/steel, electrical equipment, general engineering equipment, cement, other building materials, rubber, petroleum refining, printing, general chemicals, paints/varnish, glass/pottery, footwear, and four types of textiles
- ► Nightlights data: only after 1991

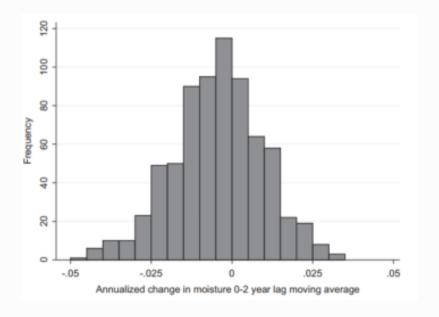




#### Data

- Climate data: moisture index
  - precipitation / potential evotranspiration (PET)
  - ► University of Delaware gridded dataset (Wilmott and Matsuura 2012)
  - ► Is there enough variability here?





## Theoretical predictions

- 1. If a city focuses on tradables: a decrease in moisture will increase labor supply
  - population growth
  - if there are agglomeration economies, we might even have productivity growth
- 2. If a city focuses on non-tradables: a decrease in moisture will at the same time increase labor supply and reduce product demand
  - smaller and unclear effects on population

# Empirical strategy

$$u_{ijt} = \beta_0 w_{ijt} + \beta_1 X'_{ij} + \beta_2 X'_{ij} w_{ijt} + \alpha_{jt} + \epsilon_{ijt}$$

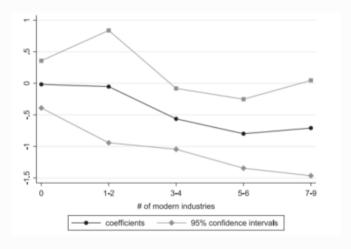
- $\triangleright$   $u_{ijt}$ : annualized growth of urban population share since last census (weird: growth of share?)
- $\triangleright$   $w_{ijt}$ : log growth of moisture (averaging the last two years), divided by the number of years (!?)
- $ightharpoonup \alpha_{jt}$ : country-year fixed effect (so only within-country variation; in fact, there are no cross-country results)
- $\triangleright$   $\beta_1$  captures heterogeneity: initial industrial capacity

#### Main Results

	(1)	(2)	(3)
Δmoisture	-0.0761 (0.180)	- 1.064*** (0.360)	- 1.164*** (0.354)
Δmoisture × (9 – #modern industries)	(0.100)	0.116*** (0.0414)	(0.00 1)
Δmoisture × (14 – #all industries)		,	0.0824*** (0.0263)
(9 – #modern industries)/1000		-0.51 (1.22)	
(14 – #all industries)/1000			0.131 (0.727)
Initial share urban/1000	-48.9*** (5.53)	-55.0*** (8.79)	-52.0*** (8.15)
In(distance to coast)/1000	1.43 (1.89)	1.55 (1.87)	1.47 (1.89)

Notes: Each column is a separate regression with 717 observations for 359 districts. The dependent variable is growth in the urbanization rate. 9 and 14 are the maximum number of modern and total industries, respectively, in any district. Robust standard errors, clustered by district, are in parentheses. All specifications include country  $^\times$  year fixed effects. \* p < 0.1, \*\*\* p < 0.05, \*\*\*\* p < 0.01.

# Non-parametric results for the heterogeneity



## Robustness Exercises

	(1)	(2)	(3)	(4)	(5)
Δmoisture	- 1.155** (0.517)	-0.359 (0.572)	- 1.165** (0.582)		
$\Delta$ moisture × (14 – #all industries)	0.0826***	(0.372)	0.0664 (0.0481)		
neighbors' Amoisture	,,		0.250 (0.685)		
neighbor's $\Delta$ moisture $\times$ (14 – own #all industries)			0.0154 (0.0515)		
Δprecipitation			(0.0012)	-1.051*** (0.378)	-0.457 (0.438)
Δtemperature				(0.570)	8.784** (3.786)
$\Delta$ precipitation $\times$ (14 – #all industries)				0.0677** (0.0284)	0.0201 (0.0338)
Δtemperature × (14 – #all industries)				(0.0284)	-0.934*** (0.279)
(14 – #all industries)/1000	0.133	-0.210	0.200	-0.022	0.746
Initial share urban/1000	(0.729) -52.0***	(0.745) -50.3***	(0.718) -52.1***	(0.738) -51.3***	(0.729) -52.9***
In(distance to coast)/1000	(8.16) 1.45	(7.82) 1.91	(8.33) 0.862	(8.09) 1.63	(7.83) 1.71
$\Delta moisture \times ln(dist.\ to\ coast)/1000$	(1.89) - 1.83 (94.1)	(1.82) 47.6 (96.7)	(1.87)	(1.90)	(1.94)
					40