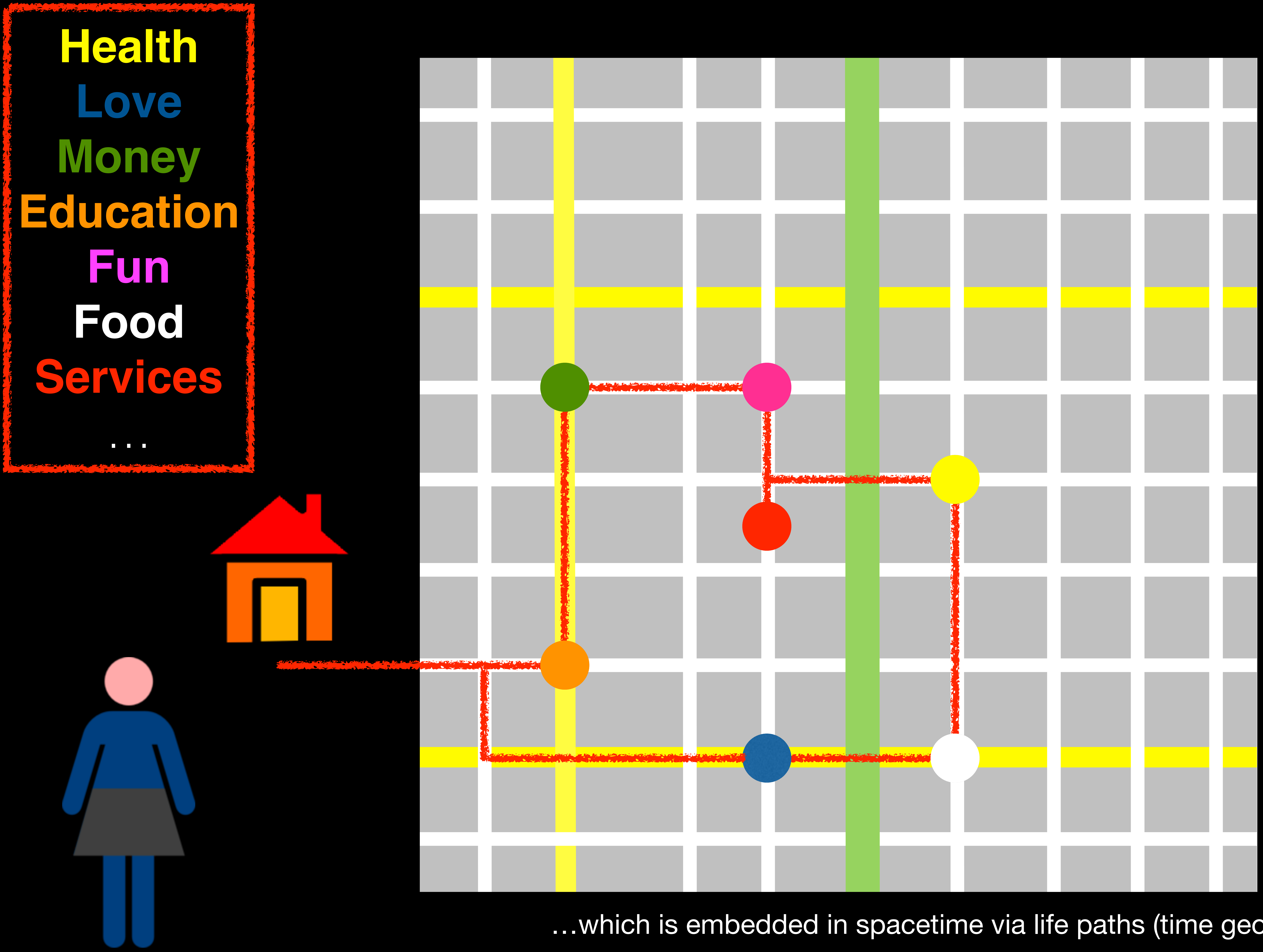
Lecture 9

The differences between cities, inequality and generating processes

9.1 The differences between cities: scale independent performance indicators

IUS 4.1

@BettencourtLuis bettencourt@uchicago.edu



IUS Fig 3.10

…which is embedded in spacetime via life paths (time geography)

We have identified many of the common factors of being a city :

Defines what a city is in general terms —> Theory

This defines a stereotypical city of a given size:

gives a frame of reference for understanding diversity and difference

—> Policy and Practice

Progress:

A wider and more comprehensive view of cities (beyond built environment, economics, geography, sociology)
Not just a 19th century industrial city
A generalizable picture across geography, levels of development, culture, political and economic systems

How about the differences **between** cities?

How to measure the effects of **history, agency** and **accident**?

How to build place-specific urban **“performance” indices**?

The Economist

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Does this make any sense?

Graphic detail | City guide

The world's most liveable cities in 2024

Our sister company has rated the best, and worst, cities in which to live

Jun 26th 2024

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To read more of The Economist's data journalism visit our Graphic detail page.

HOW DO YOU measure liveability? EIU, our sister company, came up with a formula to help companies calculate hardship allowances when relocating their staff. The annual survey rates 173 cities across five categories: stability, health care, culture and environment, education, and infrastructure. Our map and charts below show how the cities compare this year.

https://www.economist.com/graphic-detail/2024/06/26/the-worlds-most-liveable-cities-in-2024

Category 4: Education (weight: 10% of total)

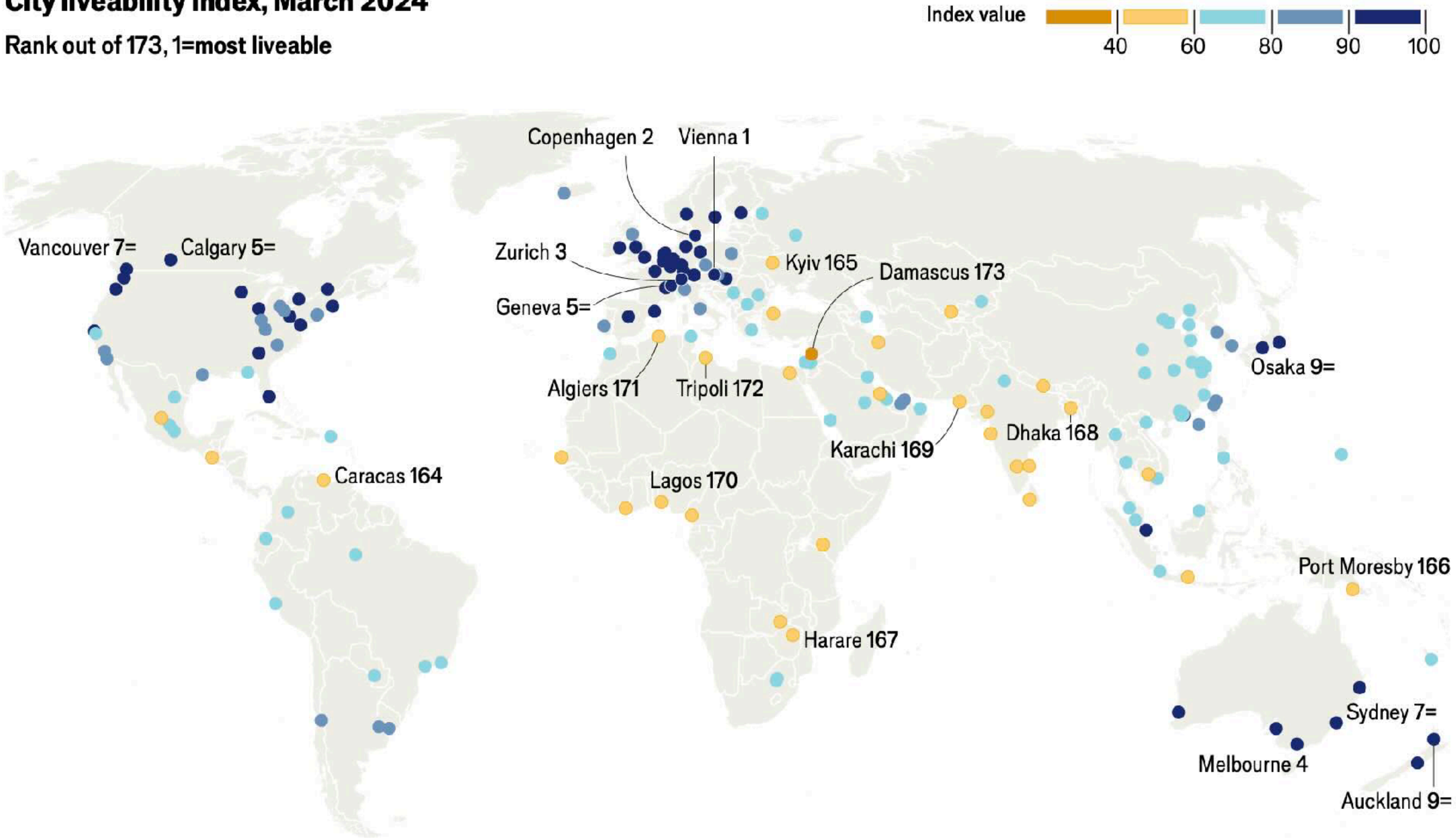
Indicator	Source
Availability of private education	EIU rating
Quality of private education	EIU rating
Public education indicators	Adapted from World Bank

Category 5: Infrastructure (weight: 20% of total)

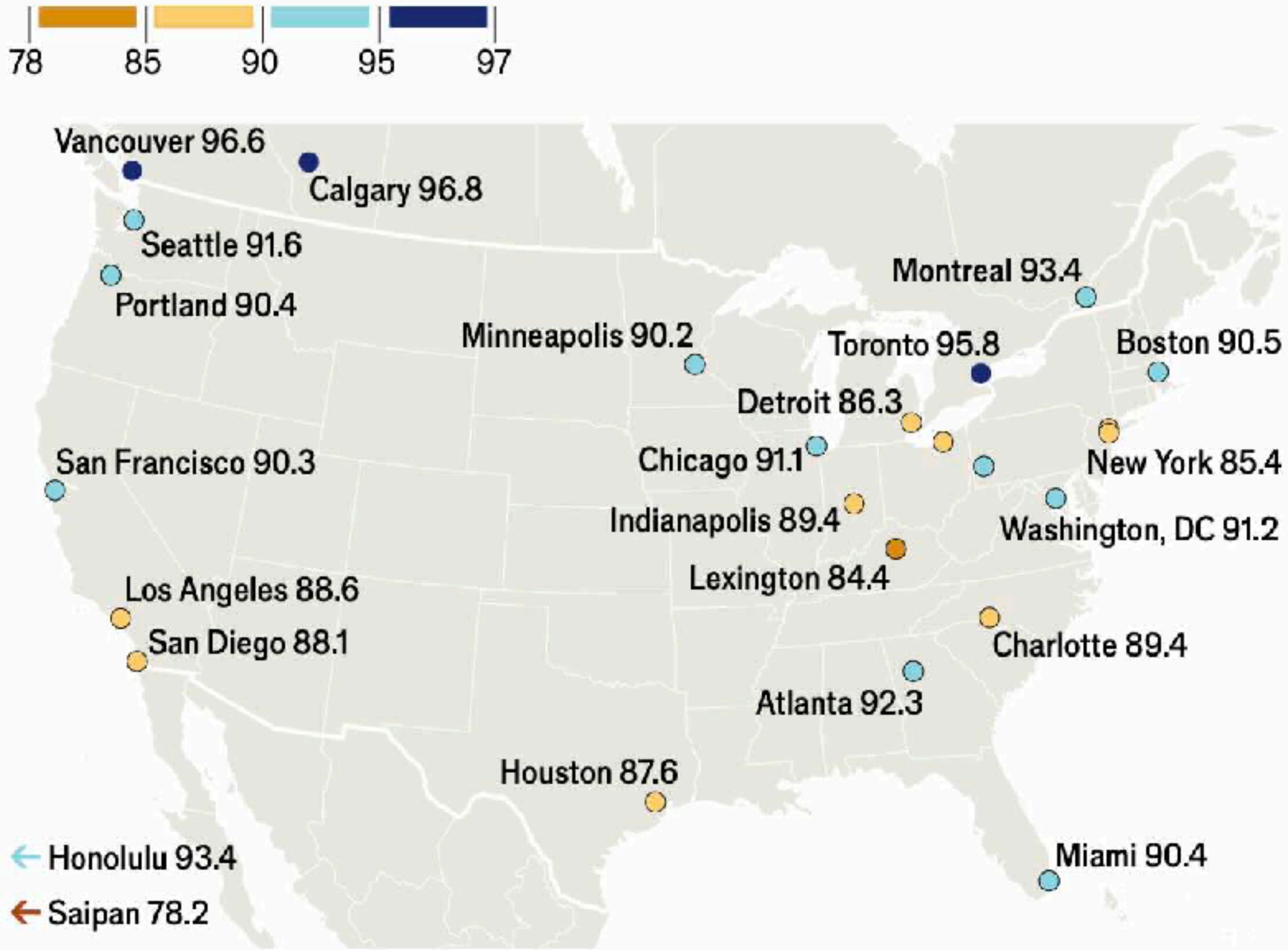
Indicator	Source
Quality of road network	EIU rating
Quality of public transport	EIU rating
Quality of international links	EIU rating
Availability of good-quality housing	EIU rating
Quality of energy provision	EIU rating
Quality of water provision	EIU rating
Quality of telecommunications	EIU rating

City liveability index, March 2024

Rank out of 173, 1=most liveable



North America*, city liveability index, March 2024



Most liveable

1	**Calgary**	96.8
2	**Vancouver**	96.6
3	**Toronto**	95.8
4=	**Honolulu**	93.4
4=	**Montreal**	93.4

Least liveable

26	**Saipan**	78.2
25	**Lexington**	84.4
24	**New York**	85.4
23	**Detroit**	86.3
22	**Houston**	87.6

Source: EIU

*EIU methodology does not include Mexico in North America.
It does includes Hawaii and the Northern Mariana Islands

Most liveable		
1	Vienna	98.4
2	Copenhagen	98.0
3	Zurich	97.1
4	Melbourne	97.0
5=	Calgary	96.8
5=	Geneva	96.8
7=	Sydney	96.6
7=	Vancouver	96.6
9=	Osaka	96.0
9=	Auckland	96.0

Least liveable		
164	Caracas	44.9
165	Kyiv	44.5
166	Port Moresby	44.1
167	Harare	43.8
168	Dhaka	43.0
169	Karachi	42.7
170	Lagos	42.2
171	Algiers	42.0
172	Tripoli	40.1
173	Damascus	30.7

Vienna took the top spot once again in 2024, earning the title of the most liveable city in the world for a third consecutive year. The Austrian capital received perfect scores in four of the index's five categories, but a lack of major sporting events contributed to its lower tally of 93.5 out of 100 in the culture and environment category. (It is far from lacking in other forms of culture.) Three other European cities made the top five: Copenhagen, Zurich and Geneva. All three are notable for their modest population size, which tends to lead to lower crime rates and less crowded roads and public-transport systems. Two Canadian cities—Calgary and Vancouver—and four in Asia-Pacific—Melbourne, Sydney, Osaka and Auckland—complete the top ten (see map).

Benchmarking cities

Per capita Indicators versus Scaling Indicators

Because Properties of Cities are Non-linear on populations size

per capita rates give us a distorted view that
mixes together general urban effects and place specific characteristics

$$Y = Y_0 N^{1+\delta} \rightarrow y = \frac{Y}{N} = Y_0 N^{\delta}$$

GDP, Wages, Crime, Patents, COVID cases, density …

tend to increase as per capita rates with city size

$$A_n = A_0 N^{1-\delta} \rightarrow a_n = \frac{A_n}{N} = A_0 N^{-\delta}$$

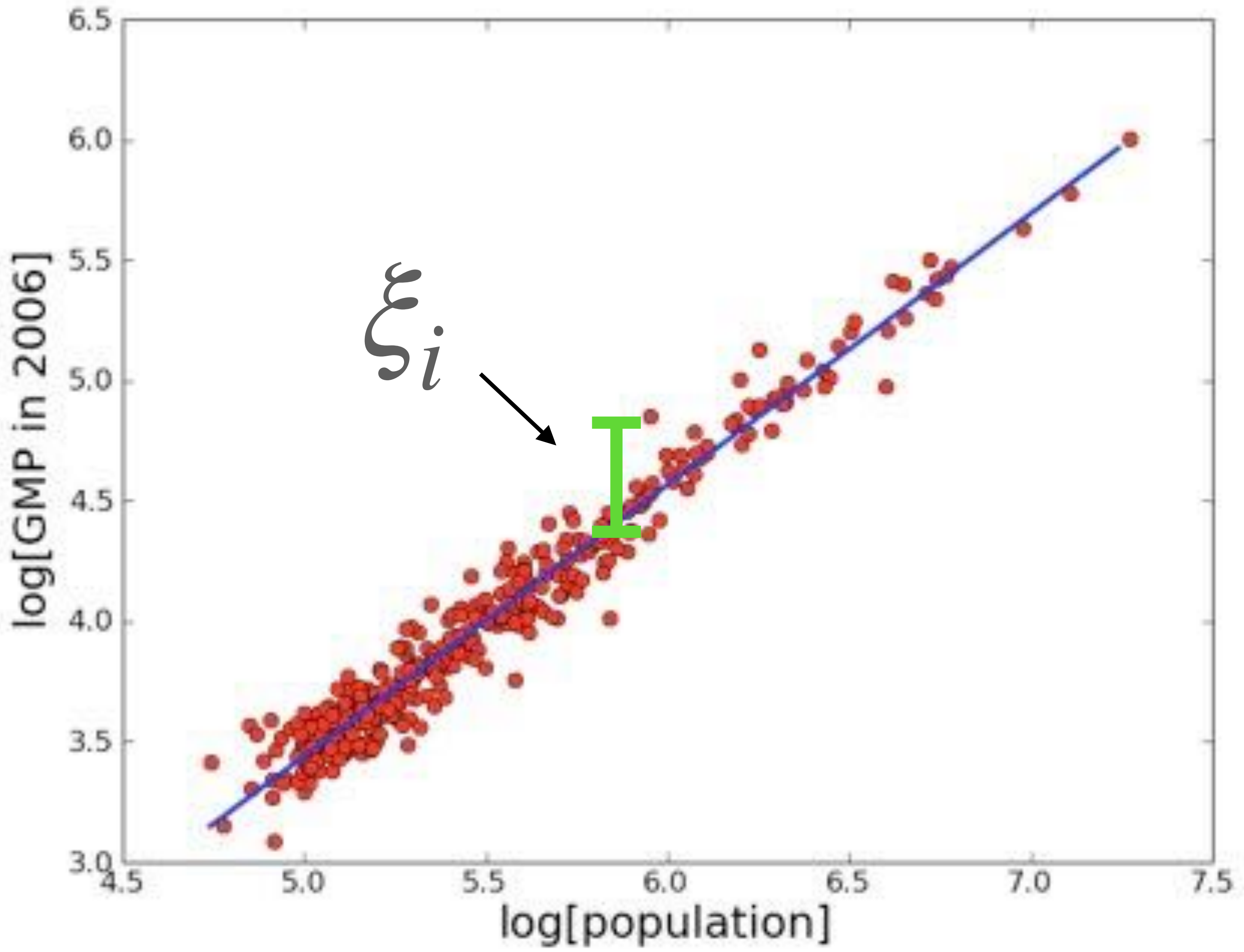
Built ares, area of roads, pipes, infrastructure

tend to decrease as per capita rates with city size

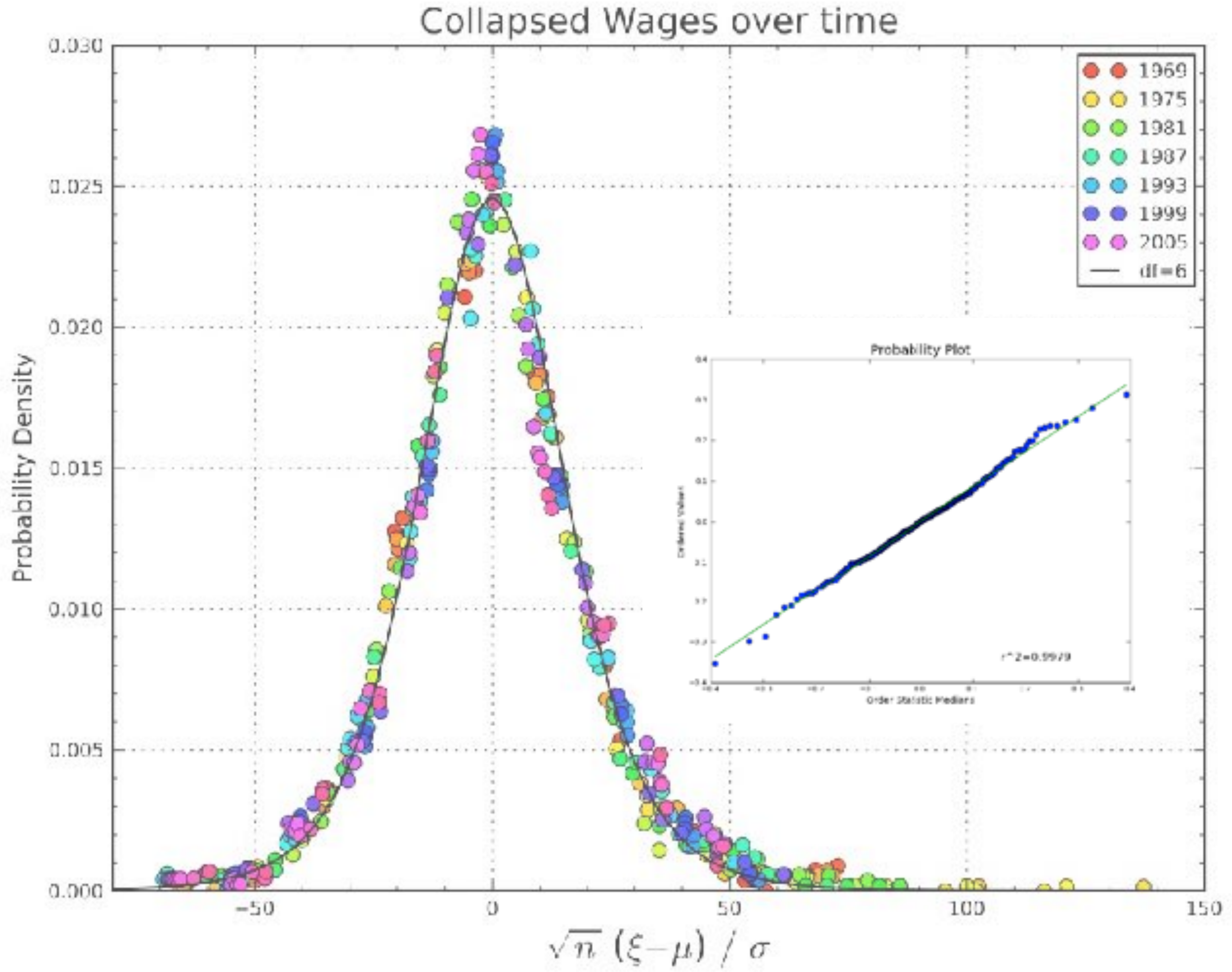
We can use scaling relations to subtract general effects and identify unique properties of each place

Deviations from Scaling

Scale Adjusted Metropolitan Indicators: SAMIs



$$Y_i = Y_0 N_i^{\beta} e^{\xi_i}$$



$$\xi_i(t) = \ln \frac{Y_i(t)}{Y_0 N^{\beta}(t)}$$

What is the structure of each city's deviation?

What is Its "local flavor" of a city?

https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0013541

Centering Data

Take the averages:

$$\langle \ln Y \rangle = \frac{1}{N_c} \sum_{i=1}^{N_c} \ln Y_i \qquad \langle \ln N \rangle = \frac{1}{N_c} \sum_{i=1}^{N_c} \ln N_i$$

Sample average

Take the scaling relation:

$$Y_i = Y_0 N_i^{\beta} e^{\xi_i} \quad \xrightarrow{\text{take the logs}} \quad \ln Y_i = \ln Y_0 + \beta \ln N_i + \xi_i$$

scaling relation

take the logs

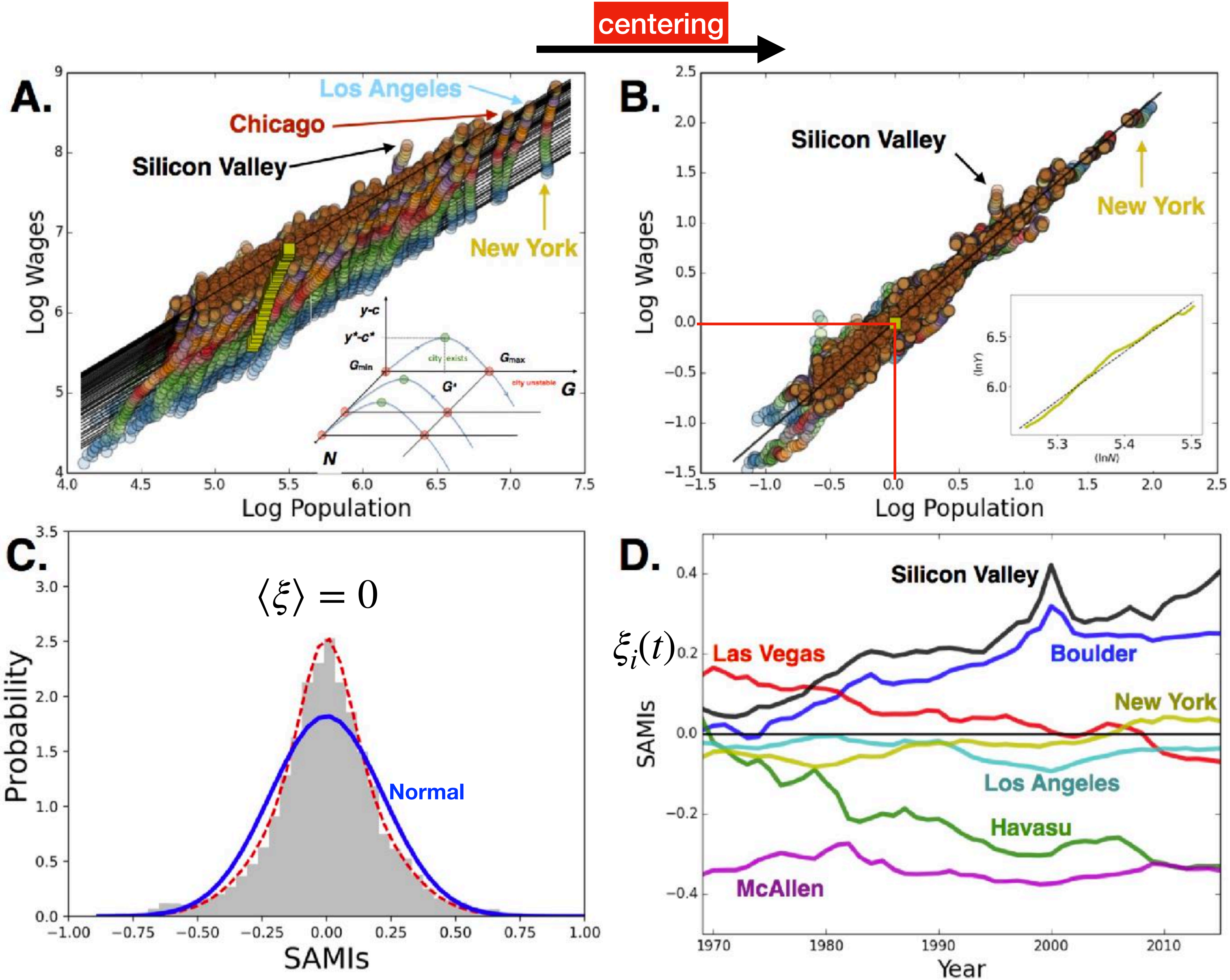
take the average

$$\langle \ln Y \rangle = \ln Y_0 + \beta \ln N_i, \qquad \langle \xi \rangle = 0$$

$$\underbrace{\ln Y_i - \langle \ln Y \rangle}_{} = \beta \ (\underbrace{\ln N_i - \langle \ln N \rangle}_{}) + \xi_i$$

Centered Variables

A linear regression centeres at (0,0). Only 1 parameter left: slope



centering
A.
Los Angeles
Chicago
Silicon Valley
New York
Log Wages
Log Population
B.
Silicon Valley
New York
Log Wages
Log Population
C.
$\langle \xi \rangle = 0$
Probability
Normal
SAMIs
D.
Silicon Valley
Las Vegas
Boulder
New York
Los Angeles
Havasu
McAllen
$\xi_i(t)$
SAMIs
Year


About
London Bridge
Visitor Information Center
Free Guides
Spring Break
Weddings
Contact
GO LAKE HAVASU
PLAY
STAY
DINE
EVENTS
PLAN
Find Your Element in Arizona's Playground
WATER
EARTH
AIR
FUN
HOTELS
Book online or call 1-800-559-2391 for assistance

The London Bridge

Take a London Bridge virtual tour and watch live streaming video of the bridge and Bridgewater Channel from our Lake Havasu Weather WebCam.

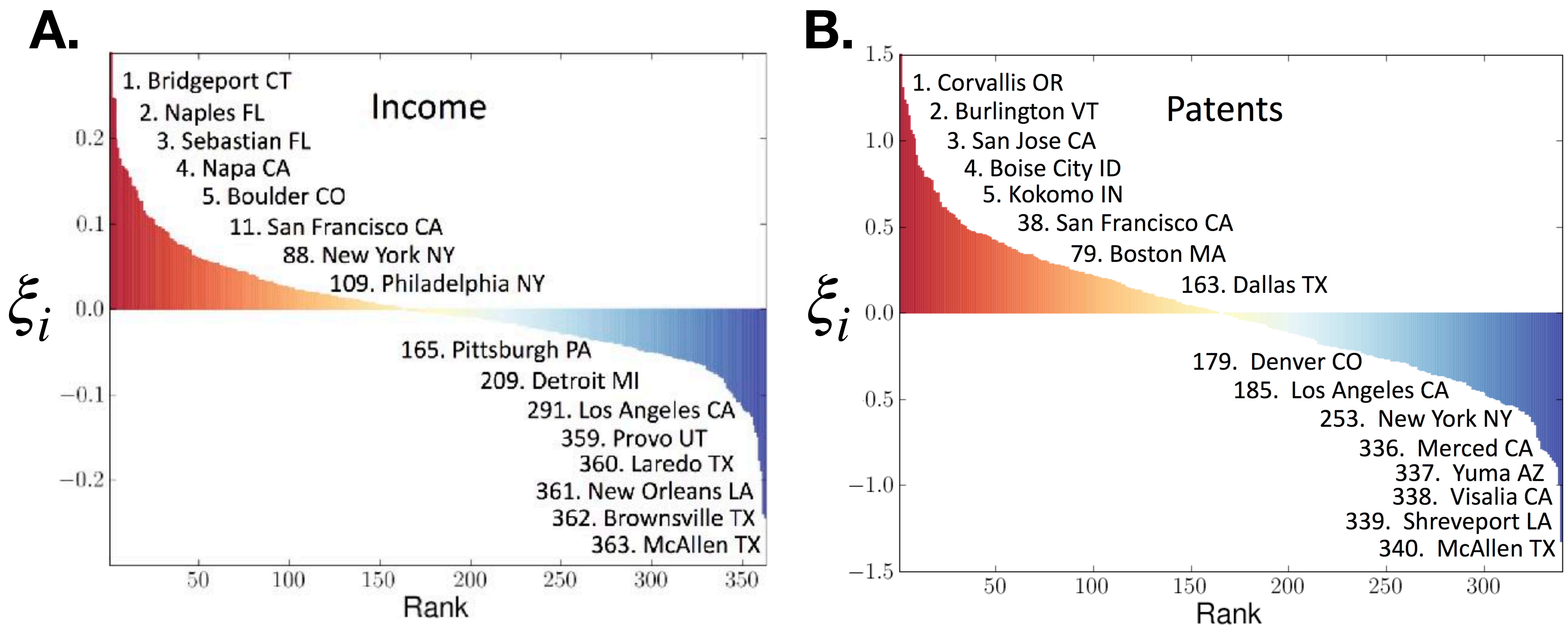
How did the world-famous London Bridge come to make its home in a remote Arizona desert city? The story began centuries earlier, over 5,400 miles away in London, England.

The London Bridge in Lake Havasu City

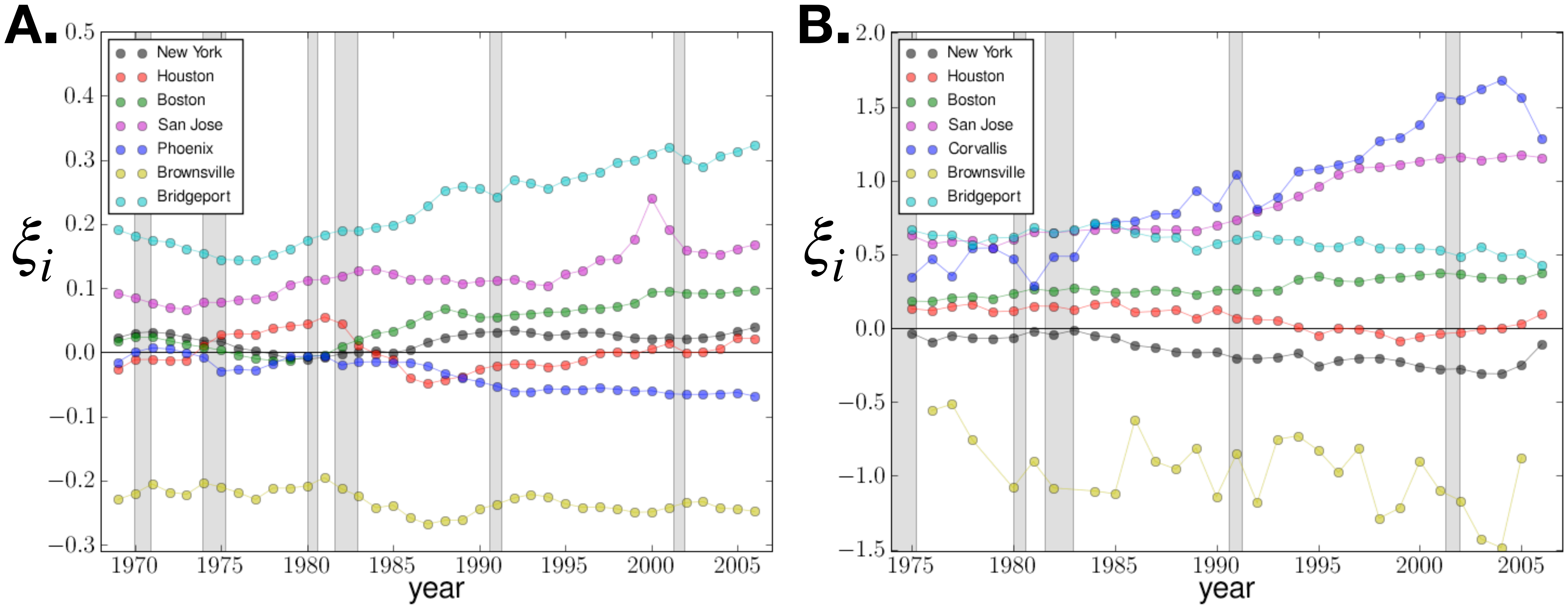
In 1967, the Common Council of the City of London began to look for potential buyers for the London Bridge. As Lake Havasu City's founder, chainsaw magnate Robert P. McCulloch, Sr. saw a once-in-a-lifetime opportunity. He believed--correctly, as history shows us--that reconstructing this massive icon in his new city would attract tourists and prospective buyers of residential lots.

McCulloch placed the winning bid of $2.4 million on April 18, 1968 (over $17 million in today's dollars). McCulloch arrived at this figure by doubling the estimated cost of dismantling the structure ($1.2 million), bringing the price to $2.4 million. He then added on $60,000, a thousand dollars for each year of his age at the time he estimated the bridge would be reconstructed in Arizona. Contrary to popular belief, McCulloch was not under the impression that he was purchasing the Tower Bridge of London.

Ranking US Metropolitan Areas by Deviations from Scaling

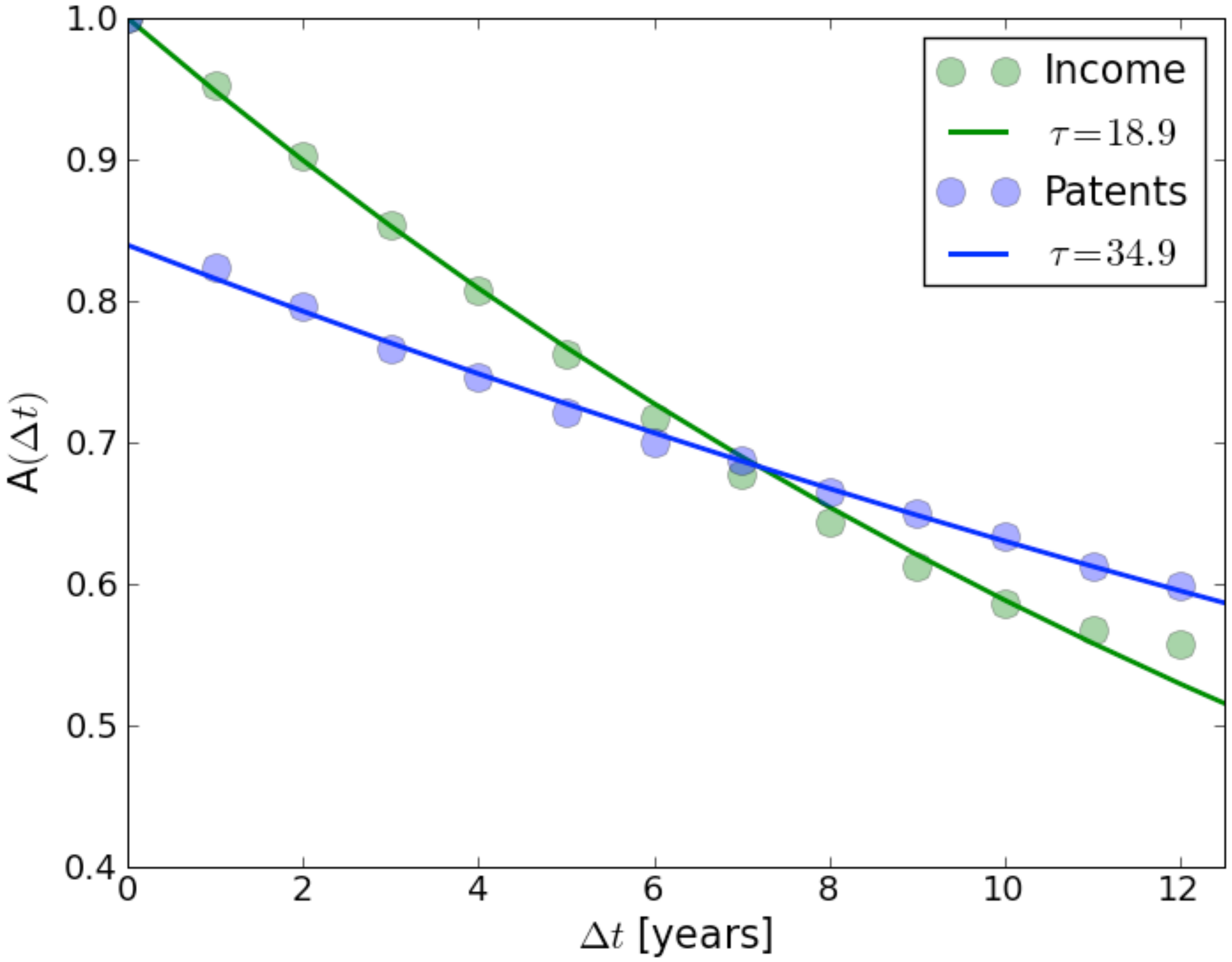


Ranking US Metropolitan Areas by Deviations from Scaling over time



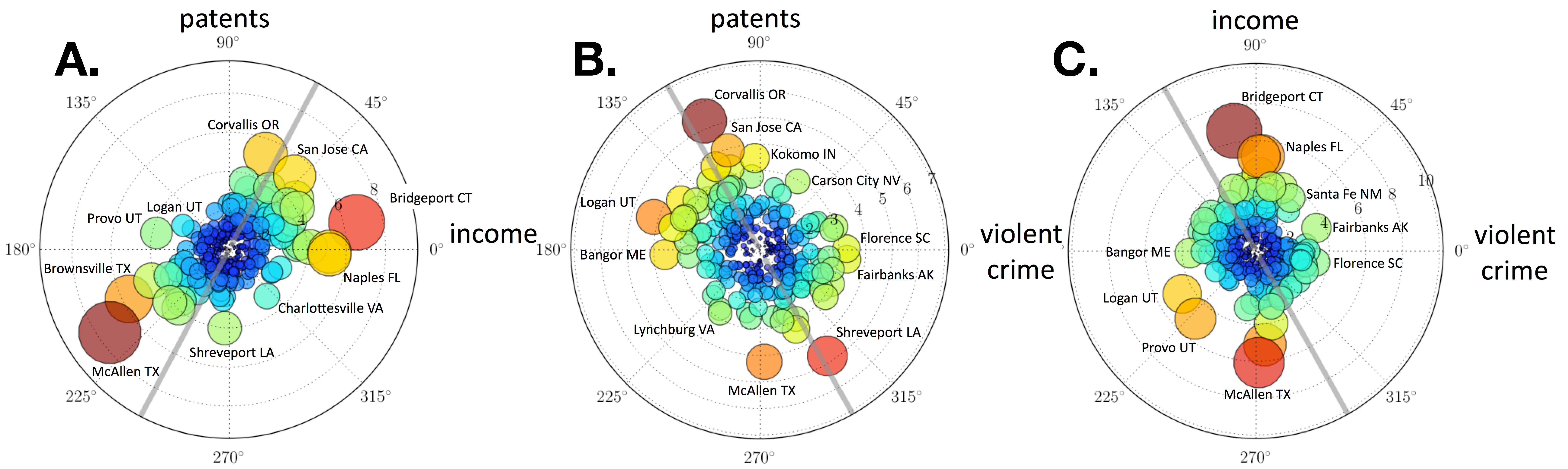
Temporal persistence

of scaling deviations

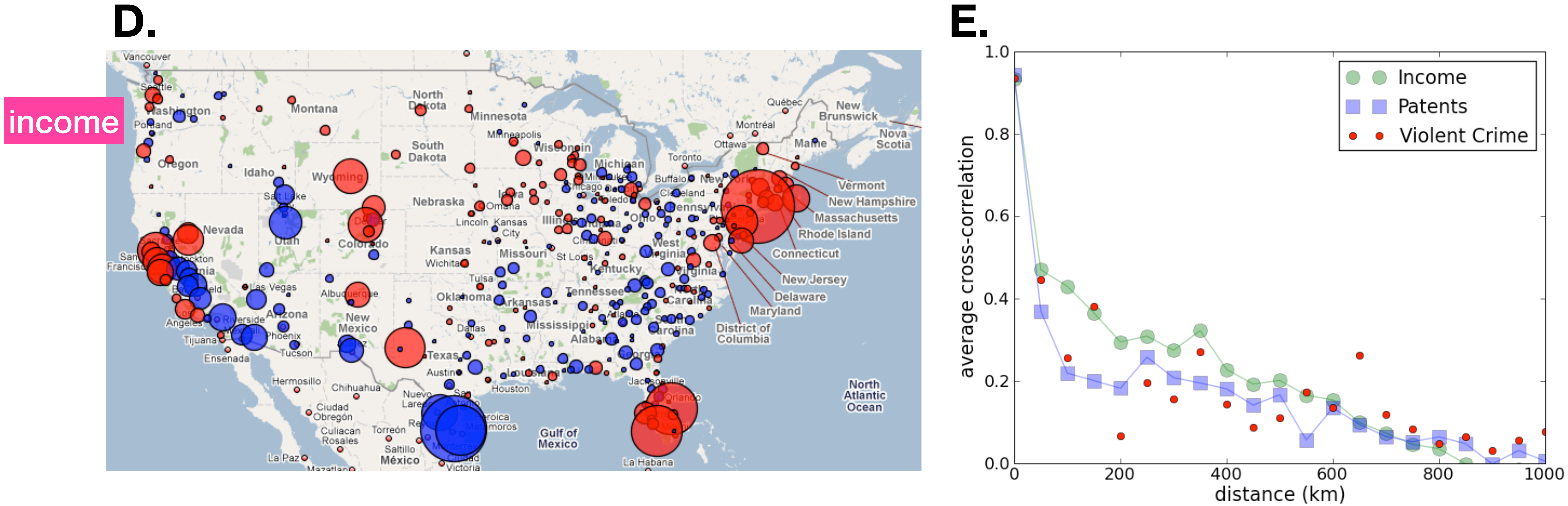


Persistence times are in the order of a few decades !

Correlations between deviations and spatial structure



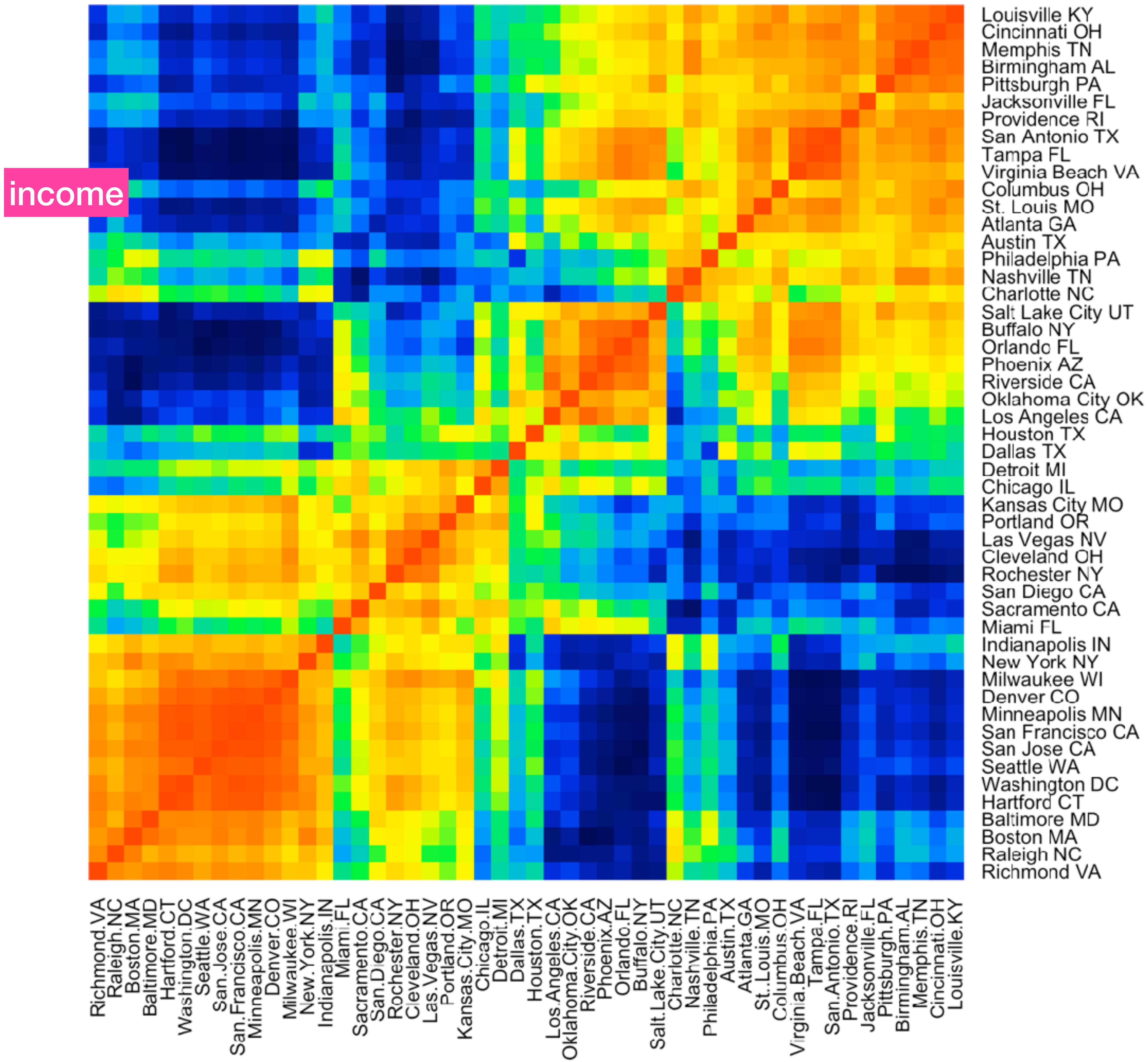
Cross correlations explain only 5-15% of the variation.



The concept of kindred cities

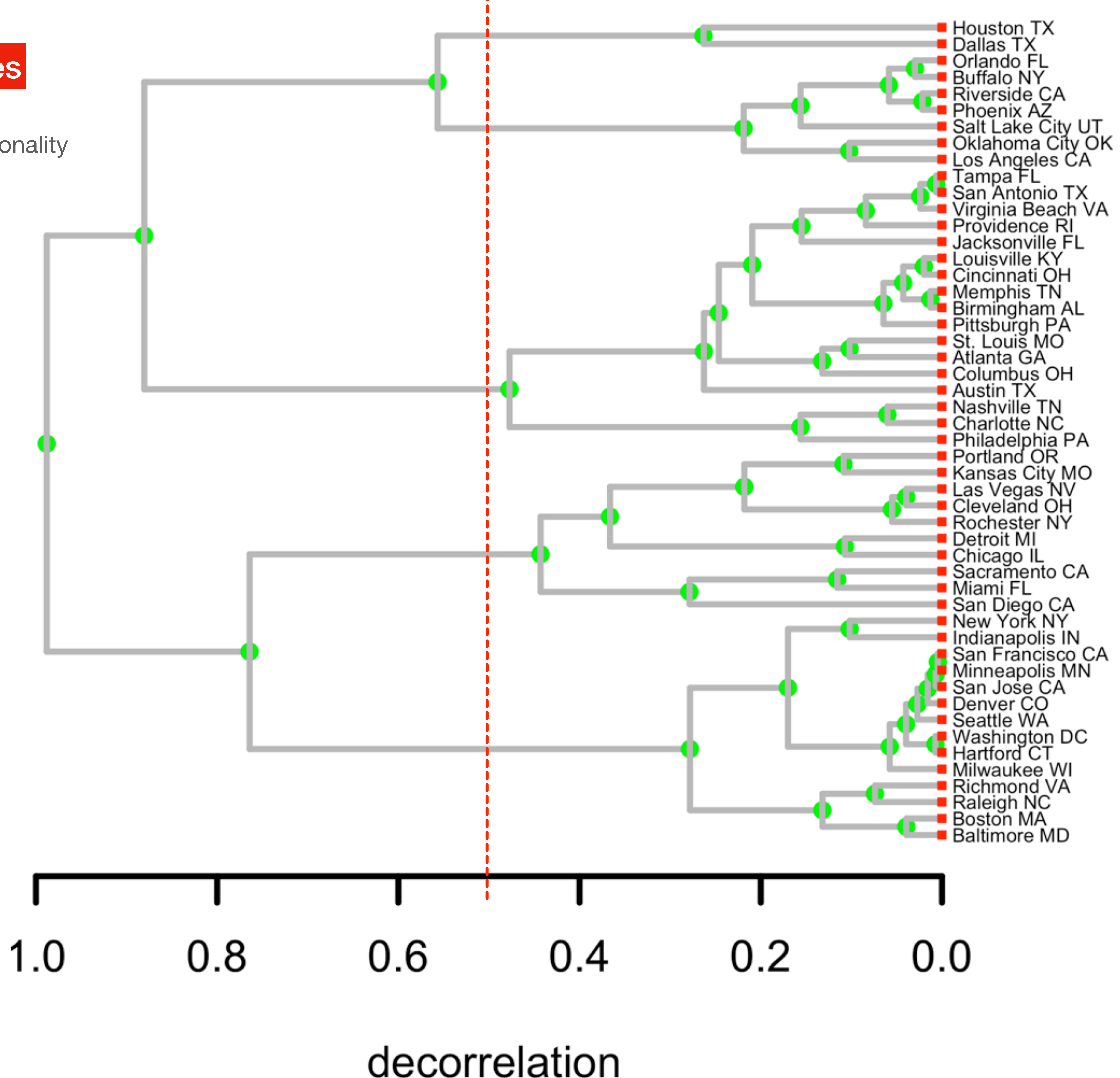
cities with similar histories of exceptionality

Heat maps from Urban History Clustering Analysis

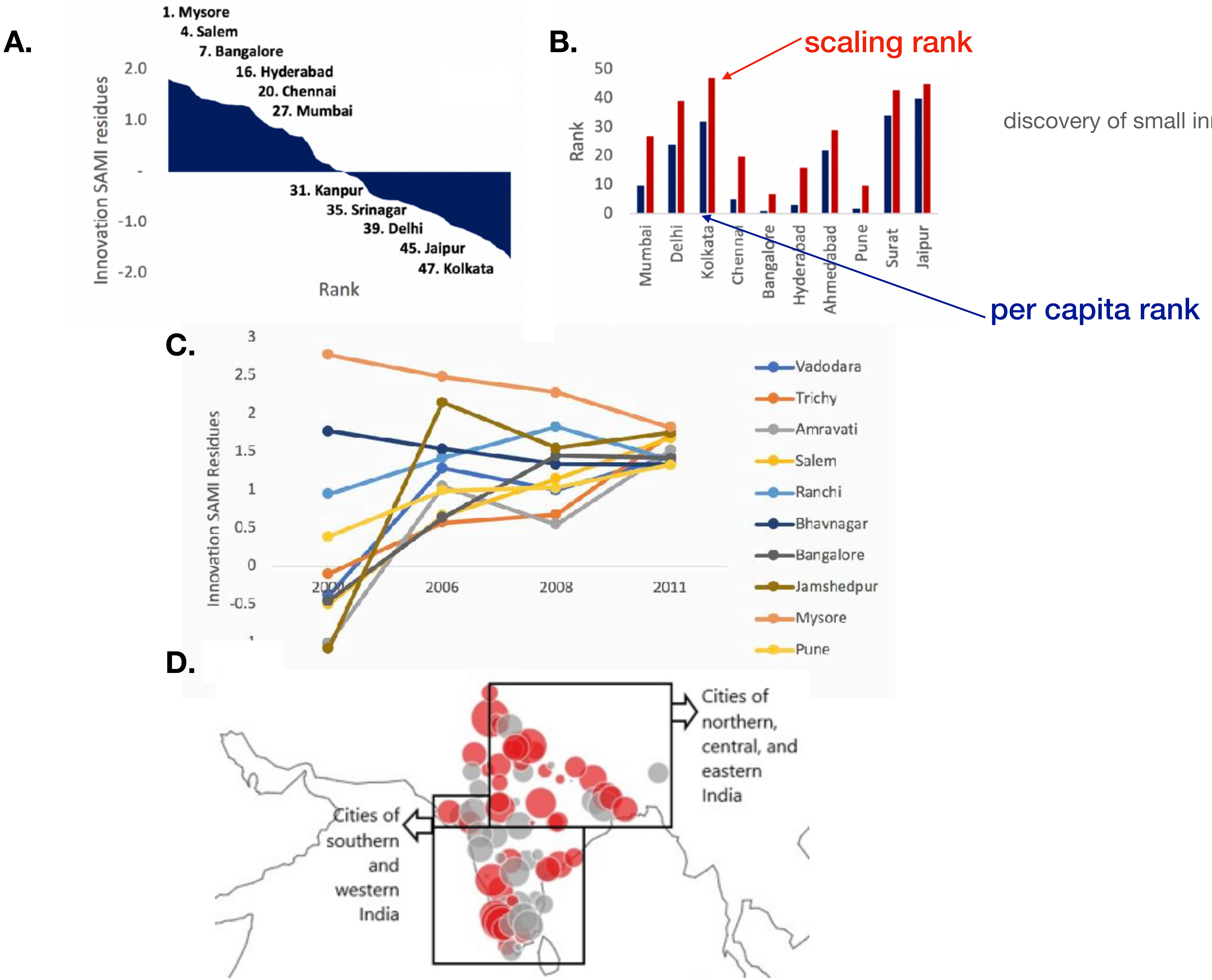


The concept of kindred cities

cities with similar histories of exceptionality



Patents in Indian Cities



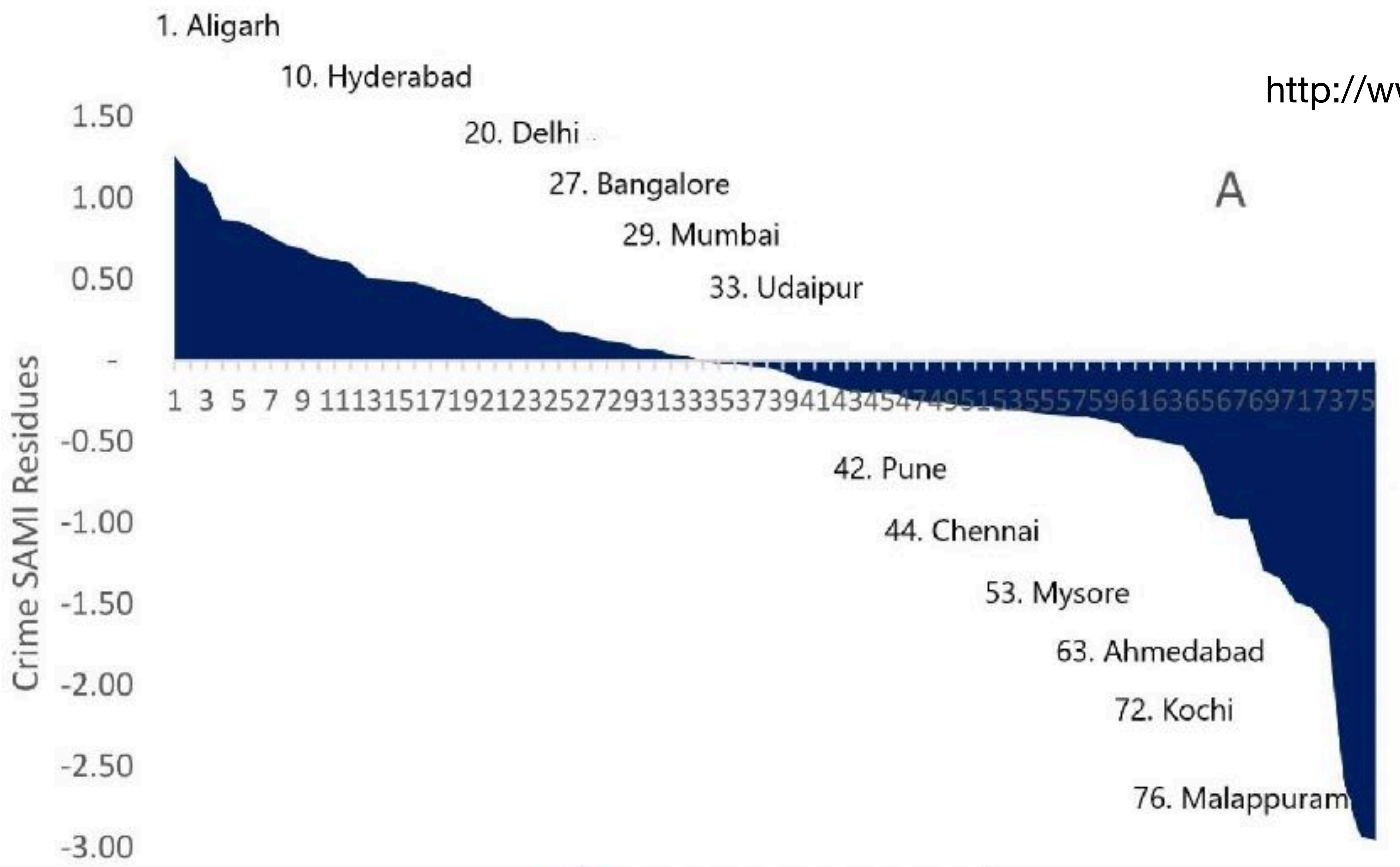
discovery of small innovative cities

http://www.royalsocietypublishing.org/doi/10.1098/rsif.2018.0758

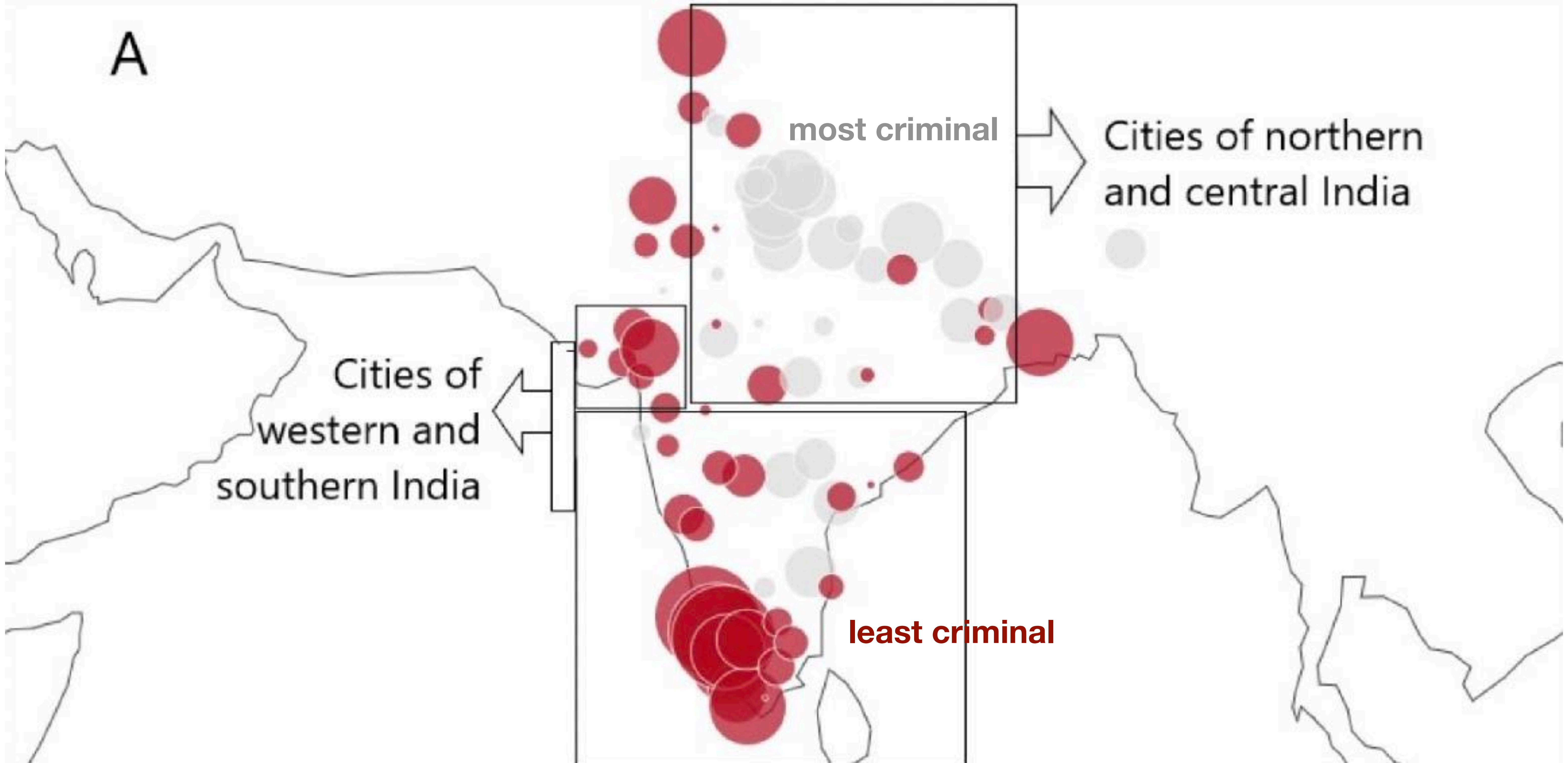
Crime in Indian Cities

http://www.royalsocietypublishing.org/doi/10.1098/rsif.2018.0758

most criminal



least criminal



Most innovative

http://www.royalsocietypublishing.org/doi/10.1098/rsif.2018.0758

Home / Lucknow / Smart city in making: Aligarh gets a chance to unlock its potential

Smart city in making: Aligarh gets a chance to unlock its potential

To tap the potential of the traditional lock industry, Aligarh will be made an International Lock City.

LUCKNOW Updated: Jul 26, 2017, 16:29 IST

S Raju/ Pradeep Saxena
Hindustan Times, Aligarh

The officials have allocated Rs 2,566 crore for the smart city project.(HT Photo)

Kerala: Malappuram tops list of world’s fastest-growing urban areas

safest

T P Nijeesh / TNN / Updated: Jan 9, 2020, 10:22 IST

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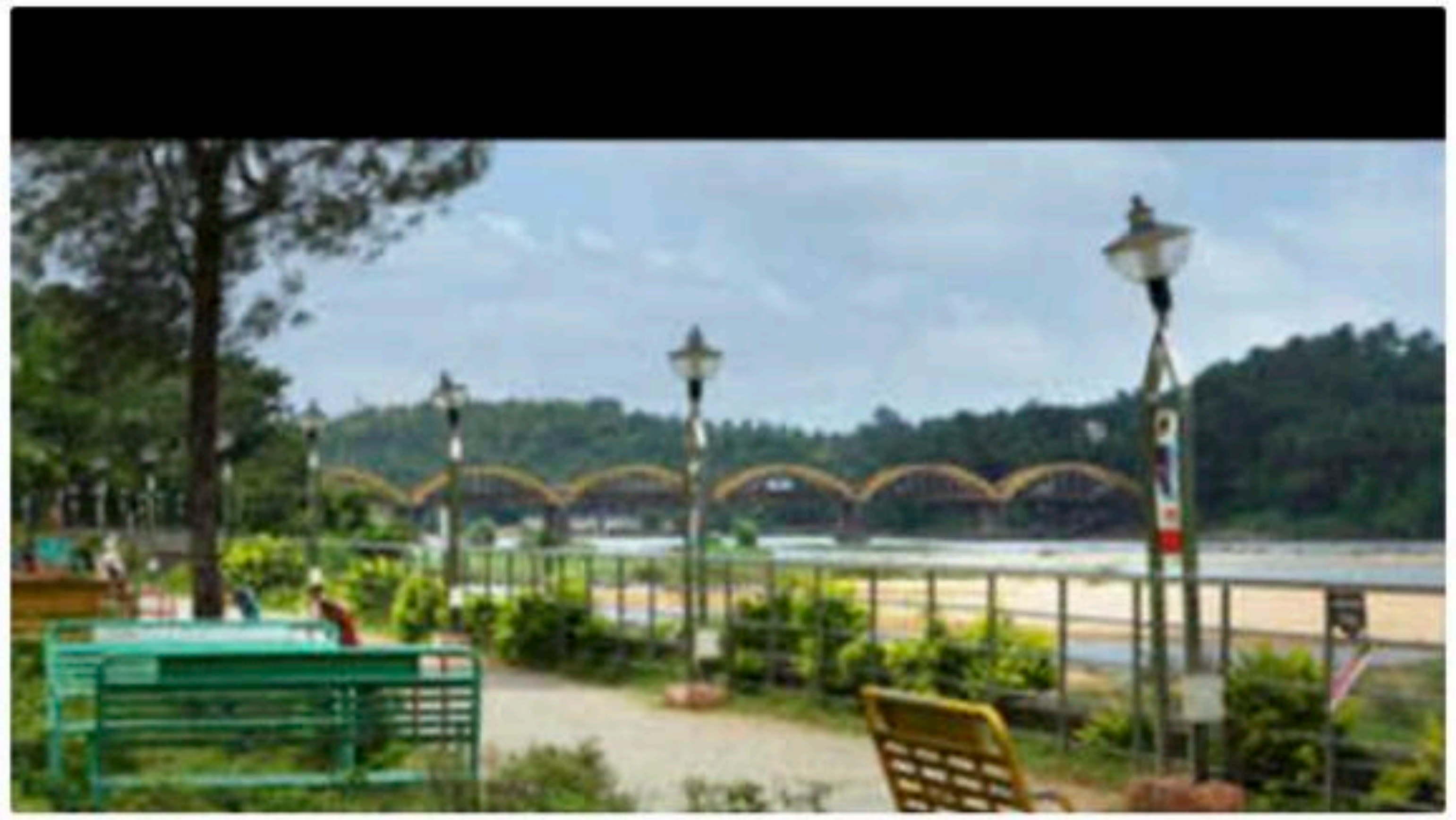
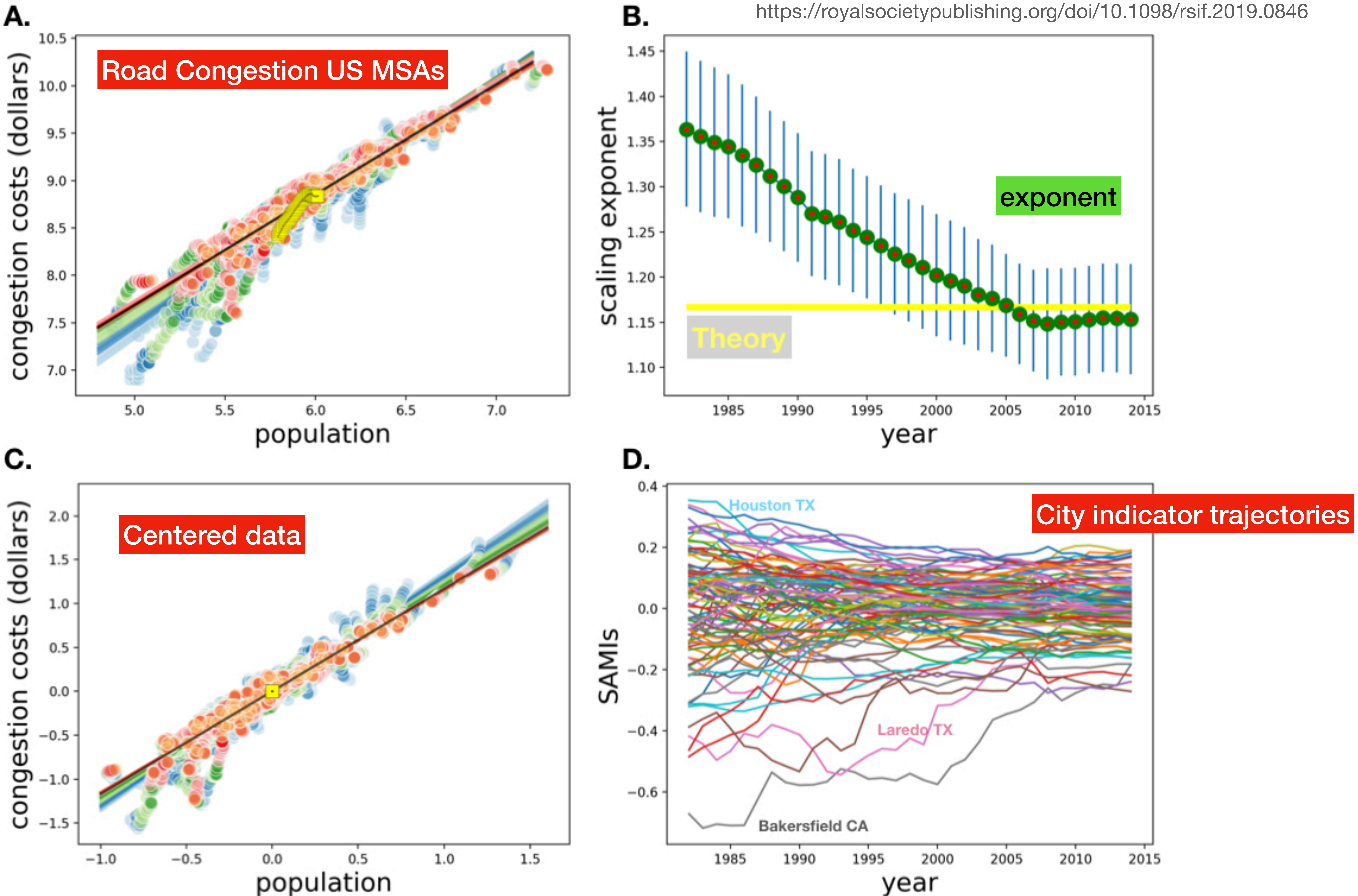
4 Tanur college project set to be fast-tracked

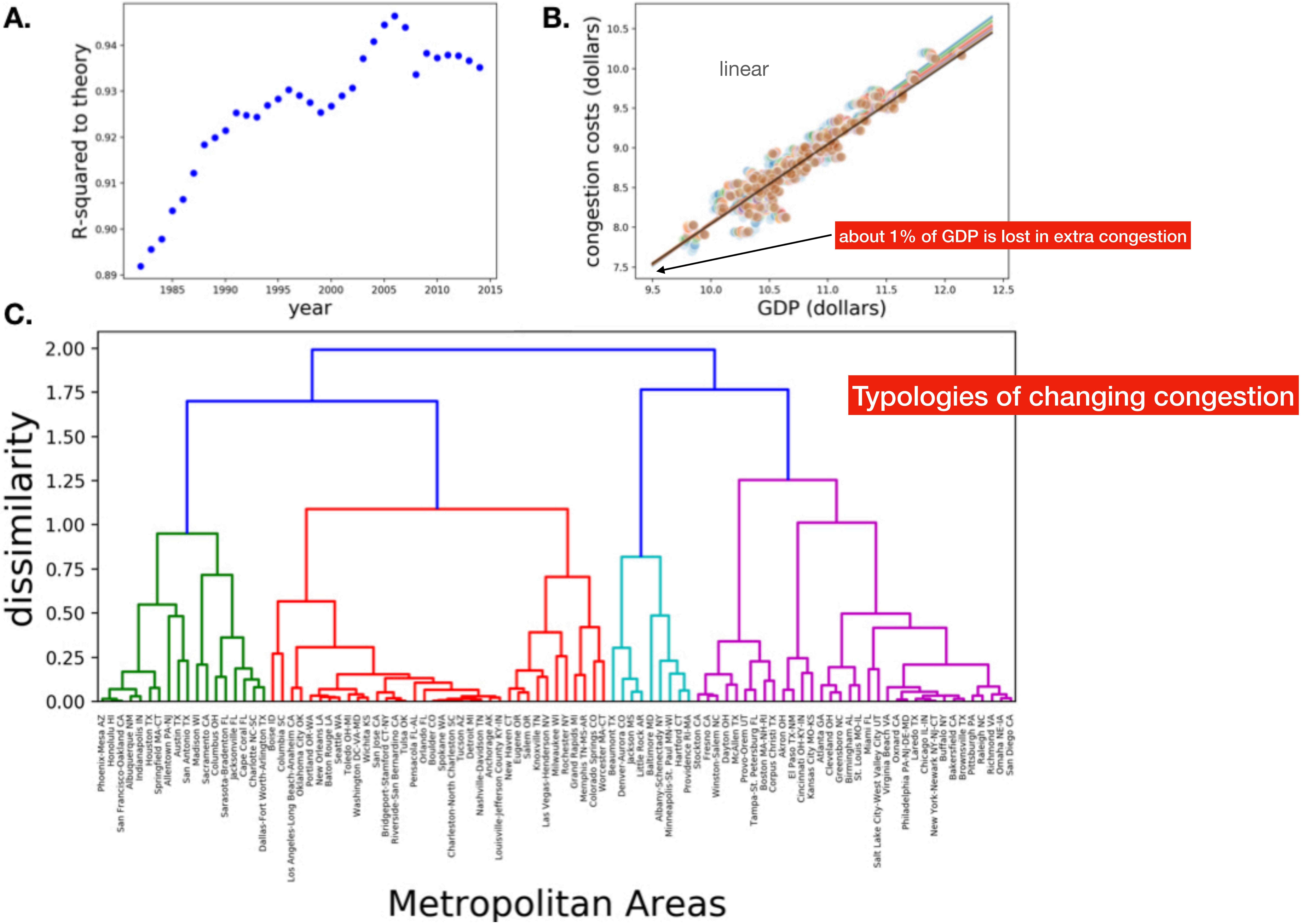


Area near Malappuram Civil Station

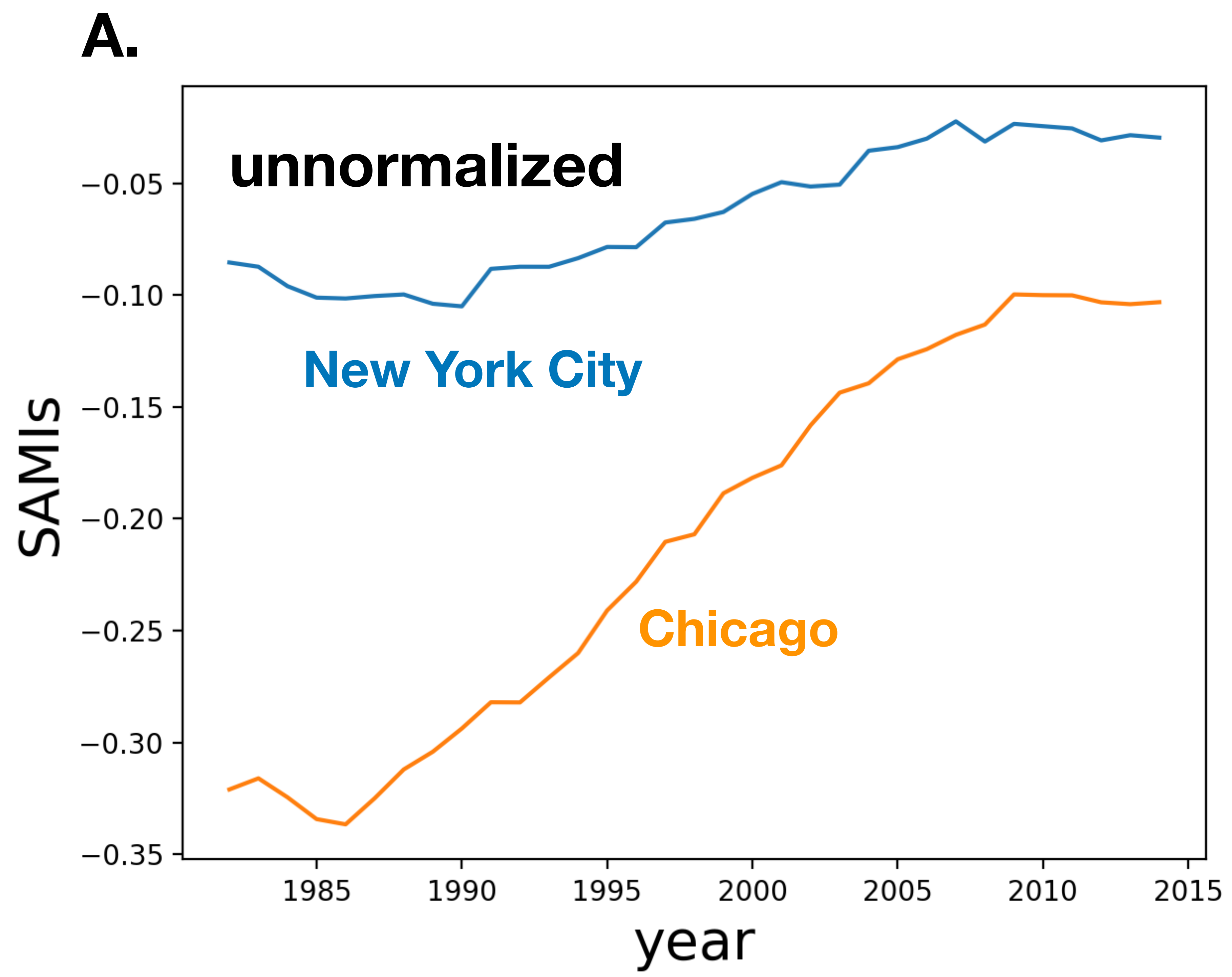
MALAPPURAM: Three of the world’s 10 fastest-growing urban areas are in Kerala, according to a survey published by The Economist

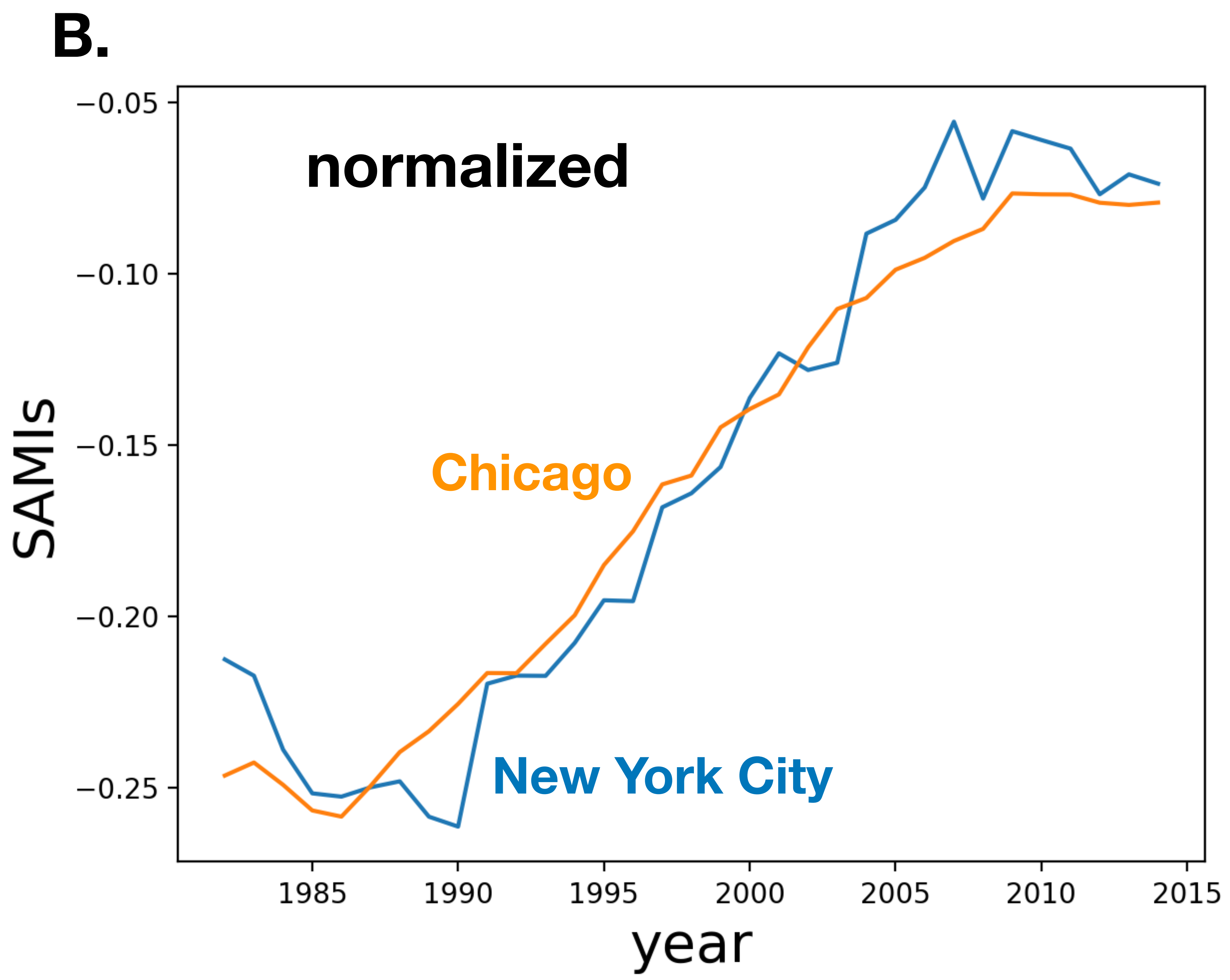
https://royalsocietypublishing.org/doi/10.1098/rsif.2019.0846




A.
R-squared to theory
0.89
0.90
0.91
0.92
0.93
0.94
1985
1990
1995
2000
2005
2010
2015
year
B.
congestion costs (dollars)
7.5
8.0
8.5
9.0
9.5
10.0
10.5
9.5
10.0
10.5
11.0
11.5
12.0
12.5
GDP (dollars)
linear
about 1% of GDP is lost in extra congestion
C.
dissimilarity
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Typologies of changing congestion
Phoenix-Mesa AZ
Honolulu HI
San Francisco-Oakland CA
Albuquerque NM
Indianapolis IN
Houston TX
Springfield MA-CT
Allentown PA-NJ
Austin TX
San Antonio TX
Madison WI
Sacramento CA
Columbus OH
Sarasota-Bradenton FL
Jacksonville FL
Cape Coral FL
Charlotte NC-SC
Dallas-Fort Worth-Arlington TX
Boise ID
Columbia SC
Los Angeles-Long Beach-Anaheim CA
Oklahoma City OK
Portland OR-WA
New Orleans LA
Baton Rouge LA
Seattle WA
Toledo OH-MI
Washington DC-VA-MD
Wichita KS
San Jose CA
Bridgeport-Stamford CT-NY
Riverside-San Bernardino CA
Tulsa OK
Pensacola FL-AL
Orlando FL
Boulder CO
Spokane WA
Charleston-North Charleston SC
Tucson AZ
Detroit MI
Nashville-Davidson TN
Anchorage AK
Louisville-Jefferson County KY-IN
New Haven CT
Eugene OR
Salem OR
Knoxville TN
Las Vegas-Henderson NV
Milwaukee WI
Rochester NY
Grand Rapids MI
Memphis TN-MS-AR
Colorado Springs CO
Worcester MA-CT
Beaumont TX
Denver-Aurora CO
Jackson MS
Little Rock AR
Baltimore MD
Albany-Schenectady NY
Minneapolis-St. Paul MN-WI
Hartford CT
Providence RI-MA
Stockton CA
Fresno CA
Winston-Salem NC
Dayton OH
McAllen TX
Provo-Orem UT
Tampa-St. Petersburg FL
Boston MA-NH-RI
Corpus Christi TX
Akron OH
El Paso TX-NM
Cincinnati OH-KY-IN
Kansas City MO-KS
Atlanta GA
Cleveland OH
Greensboro NC
Birmingham AL
St. Louis MO-IL
Miami FL
Salt Lake City-West Valley City UT
Virginia Beach VA
Oxnard CA
Philadelphia PA-NJ-DE-MD
Laredo TX
Chicago IL-IN
New York-Newark NY-NJ-CT
Buffalo NY
Bakersfield CA
Brownsville TX
Pittsburgh PA
Raleigh NC
Richmond VA
Omaha NE-IA
San Diego CA
Metropolitan Areas

Typologies are not general: they depend on measures of similarity

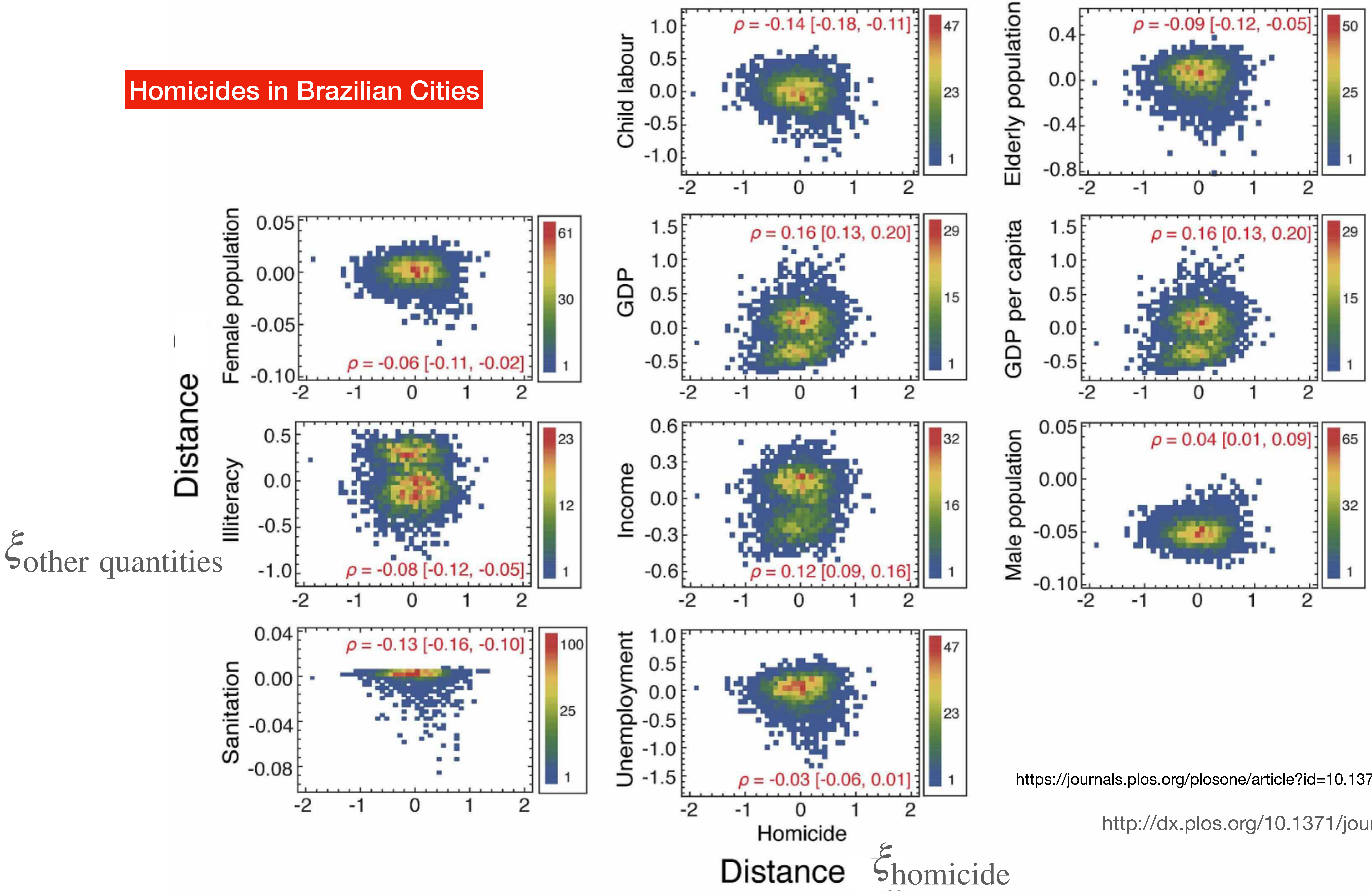




$$\vec{\xi} = (\xi(t_0), \xi(t_1), \ldots, \xi(t_n))$$

$$\vec{\xi} \rightarrow \frac{\vec{\xi}}{|\xi|} : \sum_t \vec{\xi} . \vec{\xi} = 1$$

Homicides in Brazilian Cities



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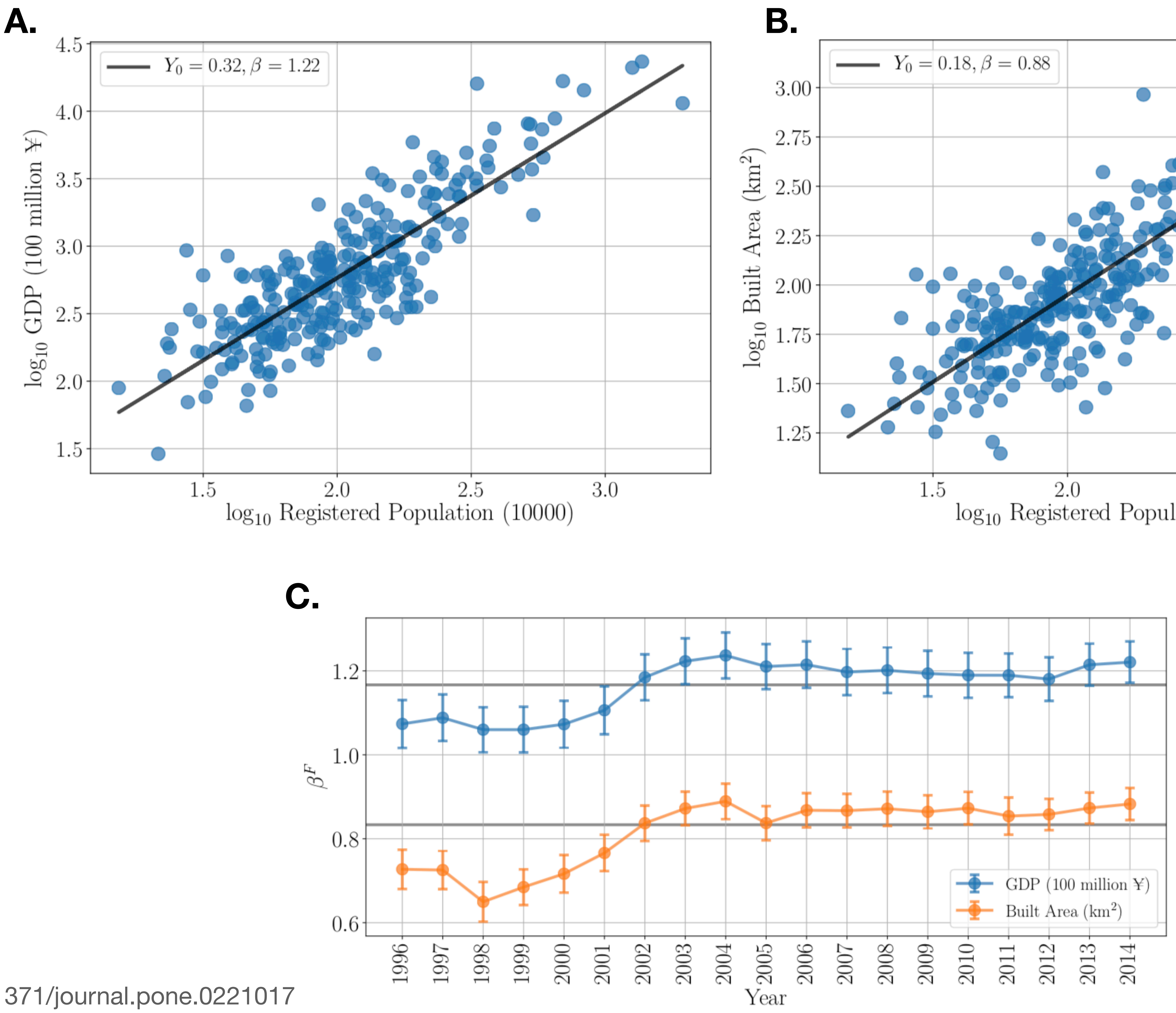
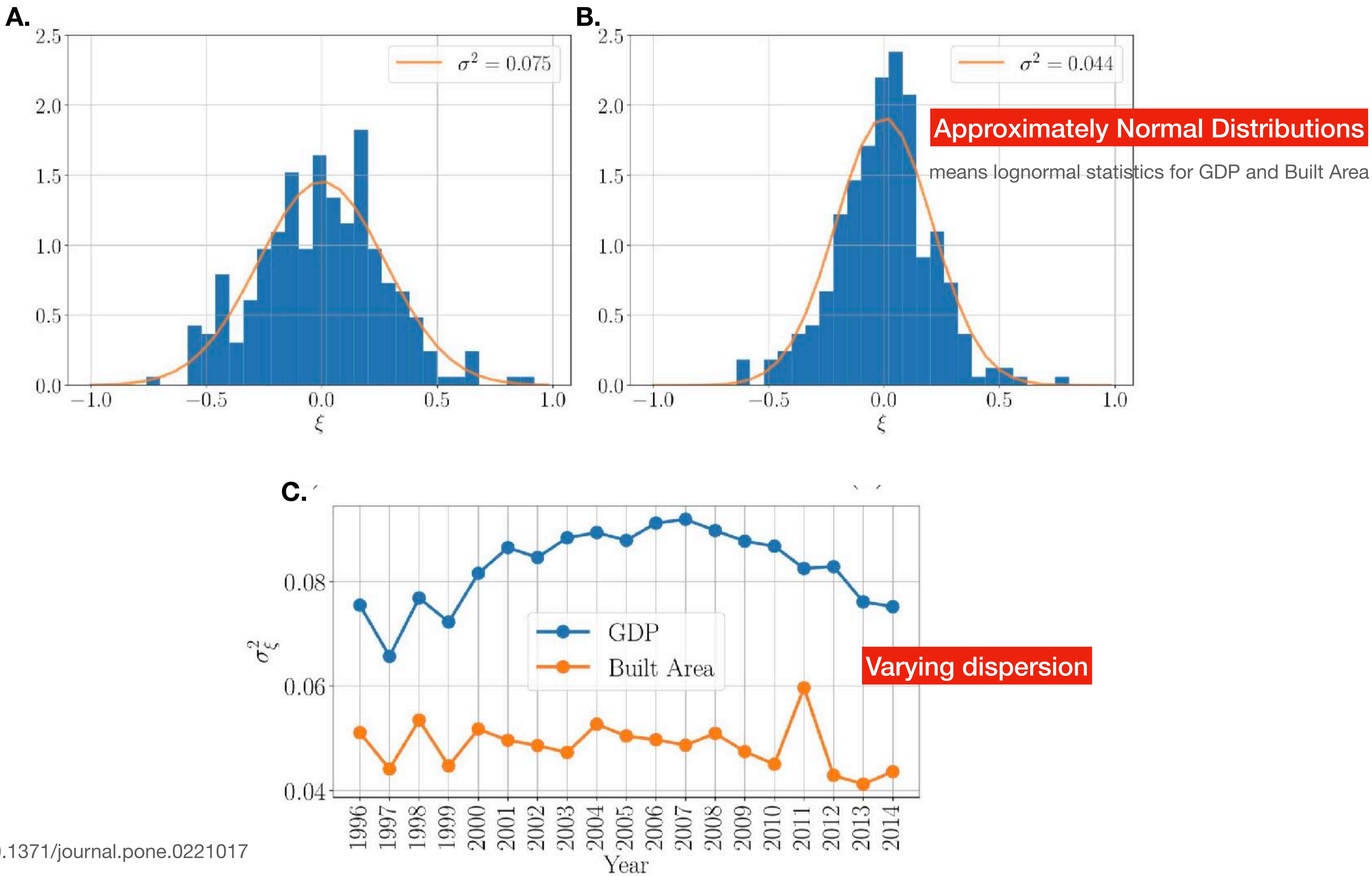
http://dx.plos.org/10.1371/journal.pone.0069580

Chinese Prefectural Cities



http://dx.plos.org/10.1371/journal.pone.0221017



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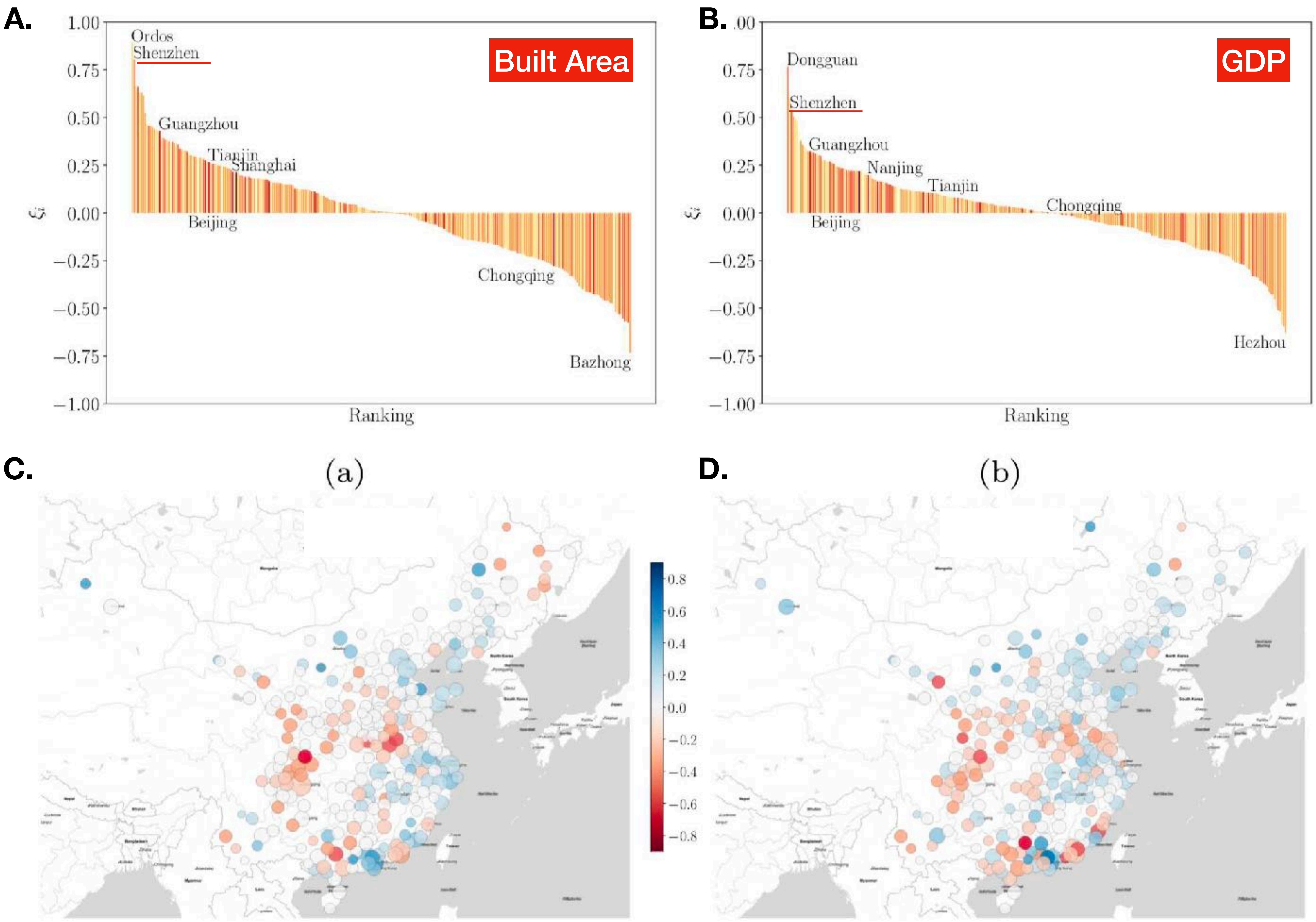


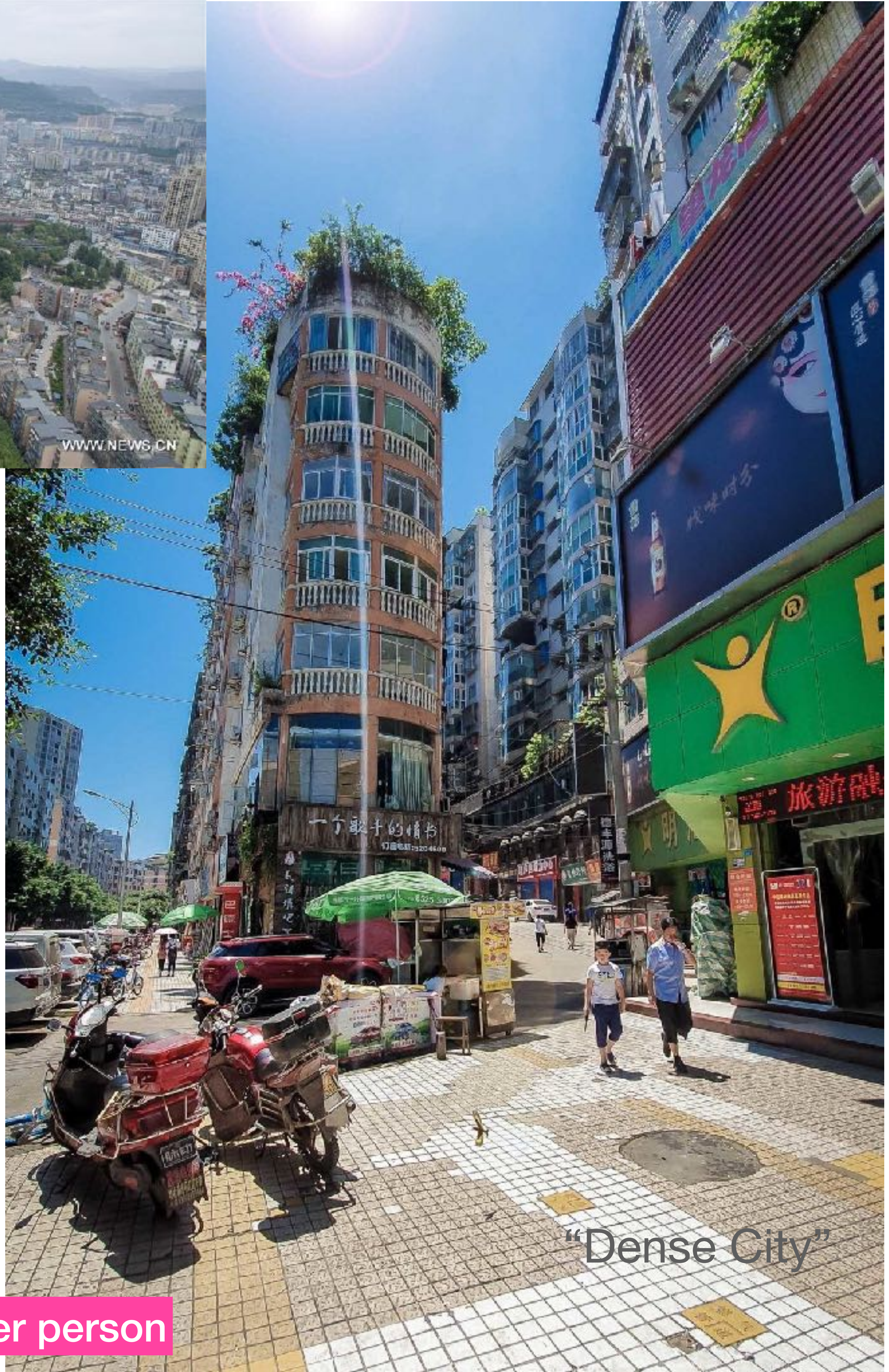
http://dx.plos.org/10.1371/journal.pone.0221017

most built area per person

Ordos, Inner Mongolia

“Ghost City”

Bazhong, China



“Dense City”

least built area per person

highest GDP per person

Dongguan

lowest GDP per person

Hezhou

The Hukou System and Population Counts in Chinese Cities

JOURNAL OF ECONOMIC SURVEYS

ARTICLE | Full Access

THE ERRONEOUS USE OF CHINA'S POPULATION AND *PER CAPITA* DATA: A STRUCTURED REVIEW AND CRITICAL TEST

John Gibson, Chao Li,

First published: 15 October 2016 | https://doi.org/10.1111/joes.12178 | Citations: 14

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Abstract

Hundreds of studies in economics misinterpret China's subnational population and *per capita* data. The most widely used population counts are of *hukou* registrations from each province, prefecture, county, or city rather than of the people living in each place and generating local gross domestic product. Over 220 million people have left their place of

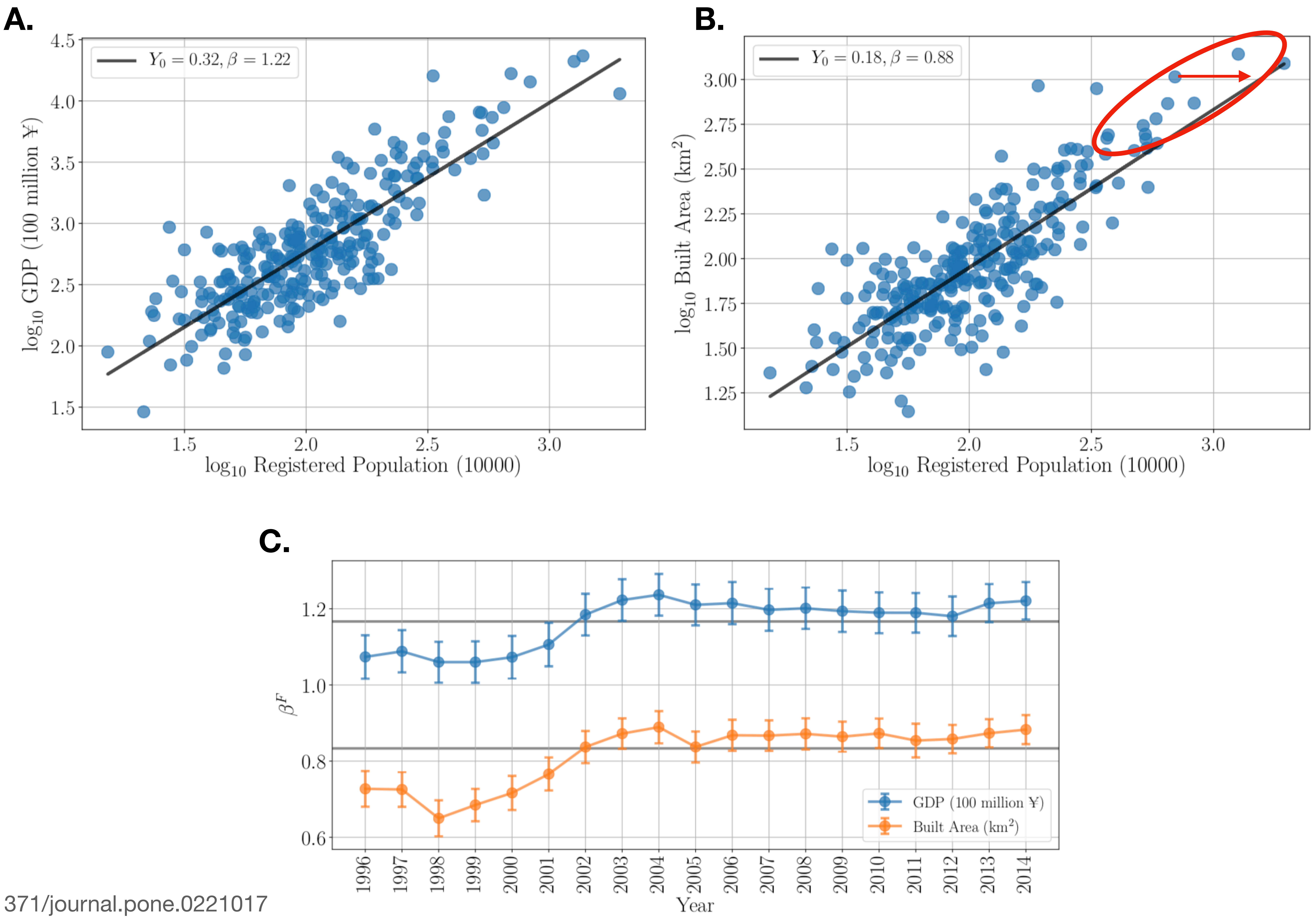
China's radical plan to limit the populations of Beijing and Shanghai

'Beautification' process ... Shanghai during the Chinese New Year holiday in February. Photograph: Imaginechina/REX/Shutterstock

Two Chinese megacities implemented population caps last year - and official data shows the policy might already be having an effect

https://www.theguardian.com/cities/2018/mar/19/plan-big-city-disease-populations-fall-beijing-shanghai

Chinese Prefectural Cities



http://dx.plos.org/10.1371/journal.pone.0221017

Estimates of actual populations from theory

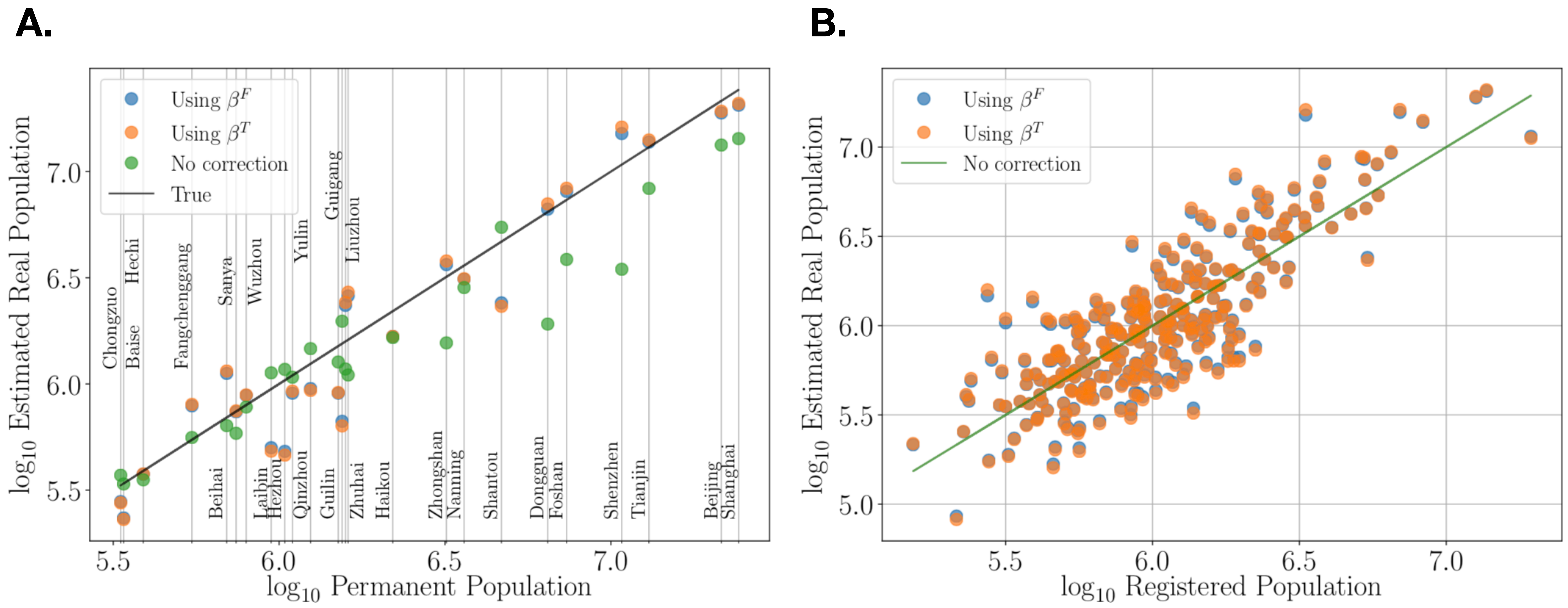
City	Resident Population	Hukou Population	Estimate β^F	Estimate β^T
Shanghai	24.26	14.29	20.54	20.93
Beijing	21.56	13.33	18.88	19.24
Tianjin	13.02	8.33	13.76	14.09
Guangzhou	11.17*	6.95	15.64	16.24
Shenzhen	10.78	3.47	15.10	16.20
Foshan	7.35	3.86	8.06	8.35
Dongguan	6.45	1.91	6.65	7.05
Shantou	4.68	5.47	2.41	2.32
Nanning	3.61	2.84	3.12	3.13
Zhongshan	3.19	1.56	3.65	3.79
Haikou	2.20	1.65	1.67	1.68
Zhuhai	1.61	1.10	2.60	2.70
Liuzhou	1.58	1.18	2.34	2.42
Guigang	1.55	1.97	0.67	0.63
Guilin	1.51	1.27	0.90	0.91
Qinzhou	1.24	1.47	0.95	0.93
Yulin	1.10	1.08	0.90	0.93
Hezhou	1.04	1.17	0.48	0.46
Laibin	0.95	1.13	0.50	0.48
Wuzhou	0.80	0.78	0.88	0.89
Sanya	0.74	0.59	0.74	0.75
Beihai	0.69	0.64	1.12	1.15
Fangchenggang	0.55	0.57	0.79	0.80
Baise	0.39	0.35	0.38	0.38
Hechi	0.34	0.34	0.23	0.23
Chongzuo	0.33	0.37	0.28	0.28

*Source: Guangzhou International.

https://doi.org/10.1371/journal.pone.0221017.t001

We can also use scaling relations as theory that helps us correct biased statistics

The actual population of large cities in China



https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0221017

So we can start to peel the onion, layer after layer of the structure of cities

From how cities work in general as networks (scaling) to the local flavor of each place (residuals)

From a general theory, to (additional!) more local theories

There will be some general aspects of diversity and inequality in cities, and some particulars and so on…

What about urban planning and policy?

RESEARCH

Beyond 'food deserts': America needs a new approach to mapping food insecurity

Caroline George and Adie Tomer
August 17, 2021

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Kaufmann et al. *EPJ Data Science* (2022) 11:50
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Scaling of urban amenities: generative statistics and implications for urban planning

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Abstract

Cities have been extensively studied as complex adaptive systems over the last 50 years. Recently, several empirical studies and emerging theory provided support for the fact that many different urban indicators follow general consistent statistical patterns across countries, cultures and times. In particular, total personal income, measures of innovation, crime rates, characteristics of the built environment and other indicators have been shown to exhibit non-linear power-law scaling with the population size of functional cities. Here, we show how to apply this type of analysis inside cities to establish universal patterns in the quantity and distribution of urban amenities such as restaurants, parks, and universities. Using a unique data set containing millions of amenities in the 50 largest US metropolitan areas, we establish

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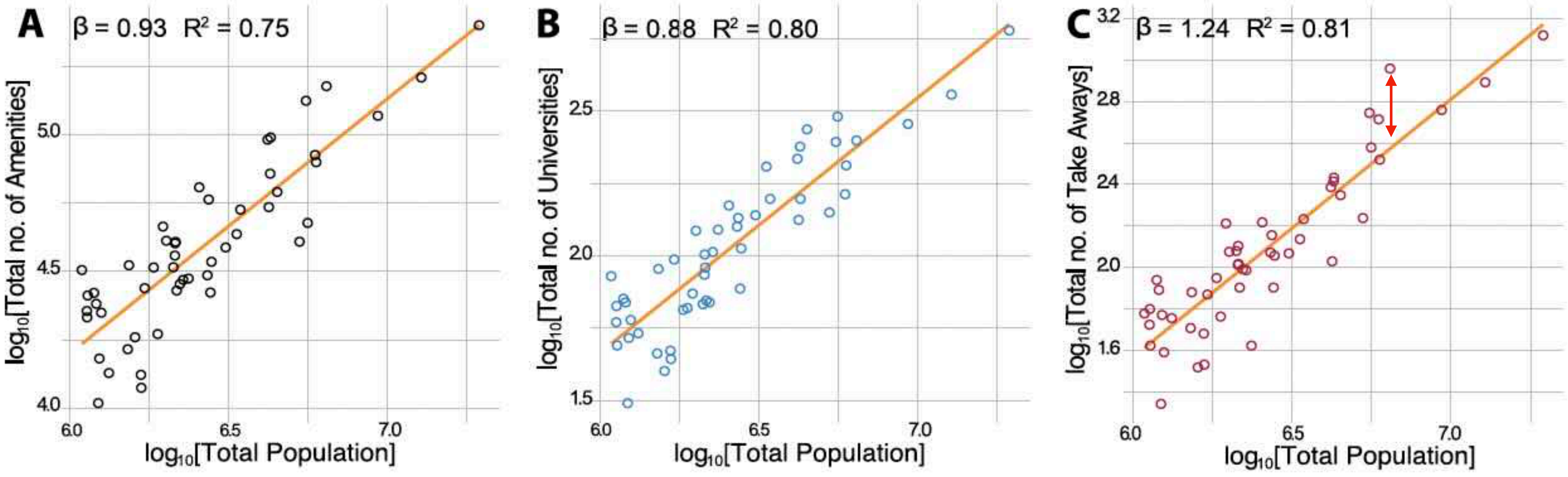


Figure 1 *Scaling of quantities of amenities and population.* The total population size (*x*-axis) and total number of amenities in a city (*y*-axis) show a good linear fit on a double logarithmic scale (**A**). The same is true for single amenity types such as universities (**B**) and take-away restaurants (**C**)

Amenity Type	adj. R^2	p-value	β [95% CI]	$\log_{10} Y_0$ [95% CI]	Amenity Type	adj. R^2	p-value	β	$\log_{10} Y_0$
Accounting	0.69	<0.001	0.89 [0.72, 1.05]	-2.80 [-3.88, -1.72]	Airport	0.40	<0.001	0.66 [0.43, 0.88]	-2.67 [-4.13, -1.21]
Amusement Park	0.53	<0.001	0.86 [0.63, 1.09]	-3.94 [-5.42, -2.47]	Art Gallery	0.64	<0.001	1.07 [0.84, 1.31]	-4.75 [-6.24, -3.27]
Atm	0.74	<0.001	0.97 [0.81, 1.14]	-3.47 [-4.52, -2.42]	Bakery	0.77	<0.001	1.14 [0.97, 1.32]	-5.04 [-6.17, -3.91]
Bank	0.54	<0.001	0.69 [0.51, 0.87]	-1.94 [-3.12, -0.77]	Bar	0.57	<0.001	0.94 [0.71, 1.18]	-3.68 [-5.17, -2.18]
Beauty Salon Spa	0.78	<0.001	1.00 [0.85, 1.15]	-3.31 [-4.28, -2.33]	Bicycle Store	0.67	<0.001	1.22 [0.97, 1.47]	-6.49 [-8.07, -4.91]
Book Store	0.74	<0.001	0.96 [0.79, 1.12]	-4.21 [-5.25, -3.17]	Cafe	0.66	<0.001	1.15 [0.92, 1.38]	-5.31 [-6.81, -3.81]
Car Dealer	0.57	<0.001	0.80 [0.60, 1.00]	-2.61 [-3.88, -1.34]	Car Rental	0.73	<0.001	1.02 [0.84, 1.19]	-4.64 [-5.77, -3.51]
Car Repair	0.70	<0.001	0.96 [0.78, 1.15]	-3.13 [-4.30, -1.96]	Car Wash	0.58	<0.001	0.87 [0.66, 1.08]	-3.75 [-5.10, -2.41]
Cemetery	0.27	<0.001	0.63 [0.34, 0.92]	-2.29 [-4.17, -0.42]	Church	0.61	<0.001	0.72 [0.55, 0.89]	-1.50 [-2.57, -0.44]
Clothing Store	0.77	<0.001	1.07 [0.90, 1.24]	-4.04 [-5.12, -2.97]	Convenience Store	0.57	<0.001	0.72 [0.54, 0.90]	-2.04 [-3.19, -0.89]
Courthouse	0.40	<0.001	0.68 [0.44, 0.91]	-2.91 [-4.42, -1.40]	Dentist	0.66	<0.001	0.99 [0.78, 1.19]	-3.24 [-4.54, -1.95]
Department Store	0.55	<0.001	0.72 [0.53, 0.91]	-2.55 [-3.74, -1.36]	Doctor	0.73	<0.001	0.90 [0.74, 1.06]	-2.12 [-3.13, -1.11]
Electrician	0.66	<0.001	0.97 [0.77, 1.17]	-3.81 [-5.08, -2.53]	Electronics Store	0.71	<0.001	1.03 [0.84, 1.21]	-3.90 [-5.11, -2.69]
Embassy	0.45	<0.001	1.11 [0.76, 1.46]	-6.24 [-8.49, -3.98]	Finance	0.65	<0.001	0.90 [0.71, 1.09]	-2.80 [-4.03, -1.57]
Fire Station	0.51	<0.001	1.01 [0.72, 1.29]	-4.81 [-6.62, -2.99]	Florist	0.77	<0.001	1.05 [0.89, 1.22]	-4.58 [-5.63, -3.53]
Funeral Home	0.50	<0.001	0.81 [0.58, 1.04]	-3.28 [-4.76, -1.80]	Furniture Store	0.71	<0.001	1.00 [0.82, 1.19]	-3.94 [-5.12, -2.75]
Gas Station	0.47	<0.001	0.76 [0.53, 0.99]	-2.93 [-4.39, -1.47]	General Contractor	0.62	<0.001	0.88 [0.68, 1.08]	-2.42 [-3.68, -1.16]
Grocery Or Supermarket	0.76	<0.001	1.01 [0.85, 1.17]	-3.95 [-5.00, -2.91]	Gym	0.78	<0.001	1.18 [1.02, 1.34]	-5.61 [-6.76, -4.46]
Hair Care	0.84	<0.001	0.94 [0.82, 1.06]	-3.75 [-4.50, -2.99]	Hardware Store	0.62	<0.001	0.87 [0.67, 1.06]	-3.37 [-4.63, -2.12]
Health	0.72	<0.001	0.92 [0.76, 1.09]	-2.72 [-3.77, -1.66]	Home Goods Store	0.70	<0.001	0.96 [0.78, 1.14]	-3.65 [-4.81, -2.50]
Hospital	0.73	<0.001	1.01 [0.84, 1.18]	-4.53 [-5.65, -3.42]	Insurance Agency	0.58	<0.001	0.82 [0.62, 1.02]	-2.24 [-3.52, -0.95]
Jewelry Store	0.72	<0.001	1.06 [0.87, 1.25]	-4.63 [-5.86, -3.41]	Laundry	0.77	<0.001	1.10 [0.93, 1.27]	-4.46 [-5.56, -3.37]
Lawyer	0.70	<0.001	0.78 [0.63, 0.92]	-1.79 [-2.73, -0.86]	Library	0.67	<0.001	0.91 [0.85, 0.97]	-3.94 [-5.12, -2.76]
Liquor Store	0.65	<0.001	1.16 [0.91, 1.40]	-5.22 [-6.78, -3.65]	Local Government Office	0.68	<0.001	0.79 [0.63, 0.94]	-2.45 [-3.43, -1.46]
Lodging	0.58	<0.001	0.87 [0.66, 1.08]	-3.14 [-4.50, -1.77]	Meal Delivery Takeaway	0.82	<0.001	1.24 [1.07, 1.41]	-5.90 [-6.99, -4.81]
Movie Rental	0.70	<0.001	1.13 [0.92, 1.34]	-5.78 [-7.13, -4.43]	Movie Theater	0.65	<0.001	0.88 [0.79, 0.97]	-3.85 [-5.04, -2.66]
Moving Company	0.69	<0.001	0.93 [0.75, 1.11]	-3.30 [-4.46, -2.15]	Museum	0.68	<0.001	0.86 [0.69, 1.03]	-3.99 [-5.08, -2.90]
Night Club	0.66	<0.001	0.98 [0.78, 1.19]	-4.28 [-5.58, -2.98]	Painter	0.63	<0.001	0.93 [0.72, 1.13]	-3.54 [-4.83, -2.25]
Park	0.65	<0.001	1.03 [0.81, 1.25]	-3.88 [-5.28, -2.48]	Parking	0.75	<0.001	1.07 [0.89, 1.25]	-4.92 [-6.05, -3.79]
Pet Store	0.61	<0.001	1.08 [0.83, 1.33]	-5.20 [-6.79, -3.61]	Pharmacy	0.59	<0.001	0.86 [0.65, 1.06]	-2.81 [-4.11, -1.51]
Physiotherapist	0.59	<0.001	0.87 [0.66, 1.07]	-3.04 [-4.37, -1.71]	Plumber	0.71	<0.001	1.03 [0.84, 1.22]	-4.22 [-5.41, -3.02]
Police	0.53	<0.001	0.94 [0.68, 1.19]	-4.35 [-5.97, -2.73]	Post Office	0.77	<0.001	1.01 [0.85, 1.17]	-4.61 [-5.64, -3.59]
Real Estate Agency	0.67	<0.001	0.99 [0.79, 1.19]	-3.34 [-4.61, -2.06]	Restaurant	0.80	<0.001	1.05 [0.90, 1.20]	-3.35 [-4.31, -2.39]
Roofing Contractor	0.55	<0.001	0.80 [0.59, 1.01]	-2.80 [-4.13, -1.47]	Rv Park	0.12	0.01	0.65 [0.18, 1.13]	-2.80 [-5.84, 0.24]
School	0.75	<0.001	1.00 [0.83, 1.16]	-3.38 [-4.42, -2.33]	Shoe Store	0.76	<0.001	1.09 [0.91, 1.27]	-4.87 [-6.01, -3.74]
Shopping Mall	0.56	<0.001	0.77 [0.57, 0.96]	-2.92 [-4.17, -1.68]	Stadium	0.67	<0.001	0.84 [0.67, 1.01]	-3.88 [-4.97, -2.80]
Storage	0.45	<0.001	0.75 [0.52, 0.99]	-2.71 [-4.23, -1.19]	Store	0.70	<0.001	0.95 [0.77, 1.12]	-2.43 [-3.57, -1.29]
Synagogue	0.63	<0.001	1.25 [0.97, 1.52]	-6.65 [-8.41, -4.89]	Travel Agency	0.73	<0.001	1.29 [1.07, 1.51]	-6.16 [-7.59, -4.73]
University	0.81	<0.001	0.88 [0.78, 0.98]	-3.62 [-4.41, -2.83]	Veterinary Care	0.47	<0.001	0.75 [0.52, 0.97]	-2.52 [-3.96, -1.09]
All Amenities	0.75	<0.001	0.93 [0.89, 0.97]	-1.38 [-2.35, -0.40]					

Table 1. Scaling for Quantities of Amenities. We report in the table the adjusted R^2 and p-value resulting from running a linear regression between the number of amenities and the number of people living in a city (both in log scale). We report also the slope and intercept of the resulting linear scaling that can be used for computing the expected number of amenities given a known population size. Results are reported for each amenity type separately and for all amenity types taken together.

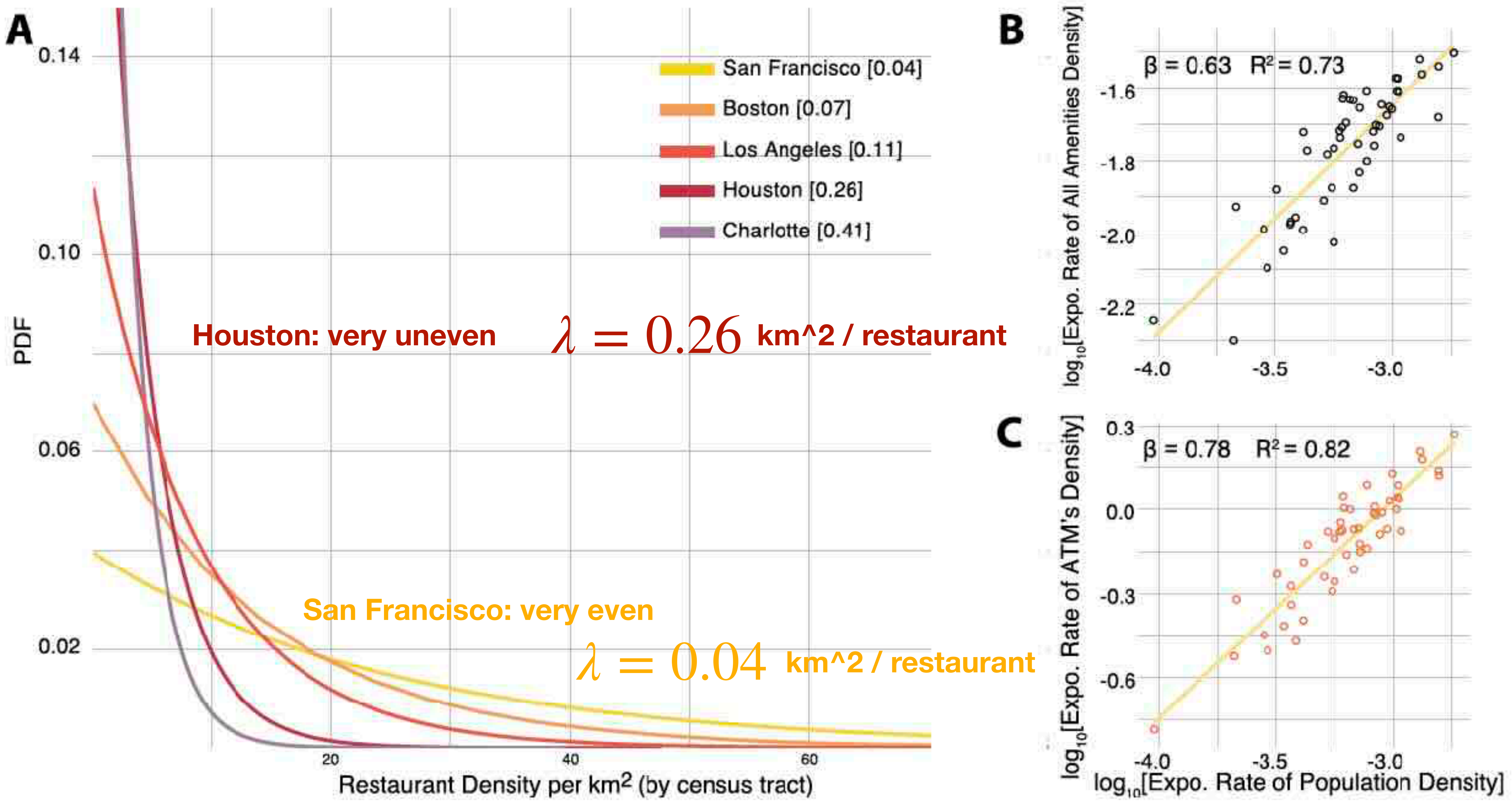
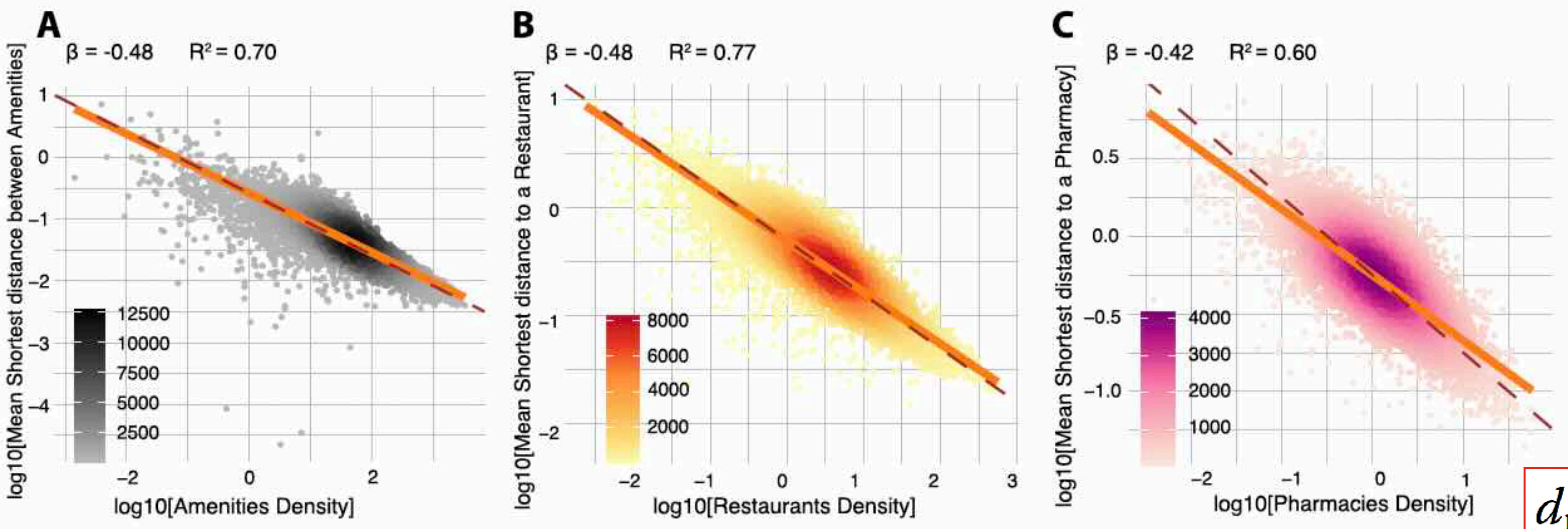


Figure 2 *Spatial distribution of amenities, by census tracts.* (**A**) The fitted exponential distribution of restaurants (by census tract). The steeper the rate of decay (Charlotte), the more unevenly restaurants are distributed. Lower rates of decay (San Francisco) mean a more even distribution of restaurants. A comparison of the fitted and actual distributions are provided in Additional file 1, Figure S1. (**B**) The exponential rate of decay for population density (*x*-axis) and the exponential rate of decay for amenity density in a city (*y*-axis) show a good fit on a double logarithmic scale ($R^2 = 0.73$). (**C**) The same is true for a single amenity type such as ATMs ($R^2 = 0.82$)



$$d_{\min} = x^{-1/2}$$

Figure 3 *Scaling of mean shortest distance between amenities and density of amenities*. The orange line shows the best fit line while the dashed red line represents the –0.5 slope line. (**A**) Scaling of mean shortest distances and densities of all amenities. (**B**) Scaling of mean shortest distances between all amenities to restaurants and densities of restaurants. (**C**) Scaling of mean shortest distances between all amenities to pharmacies and densities of pharmacies

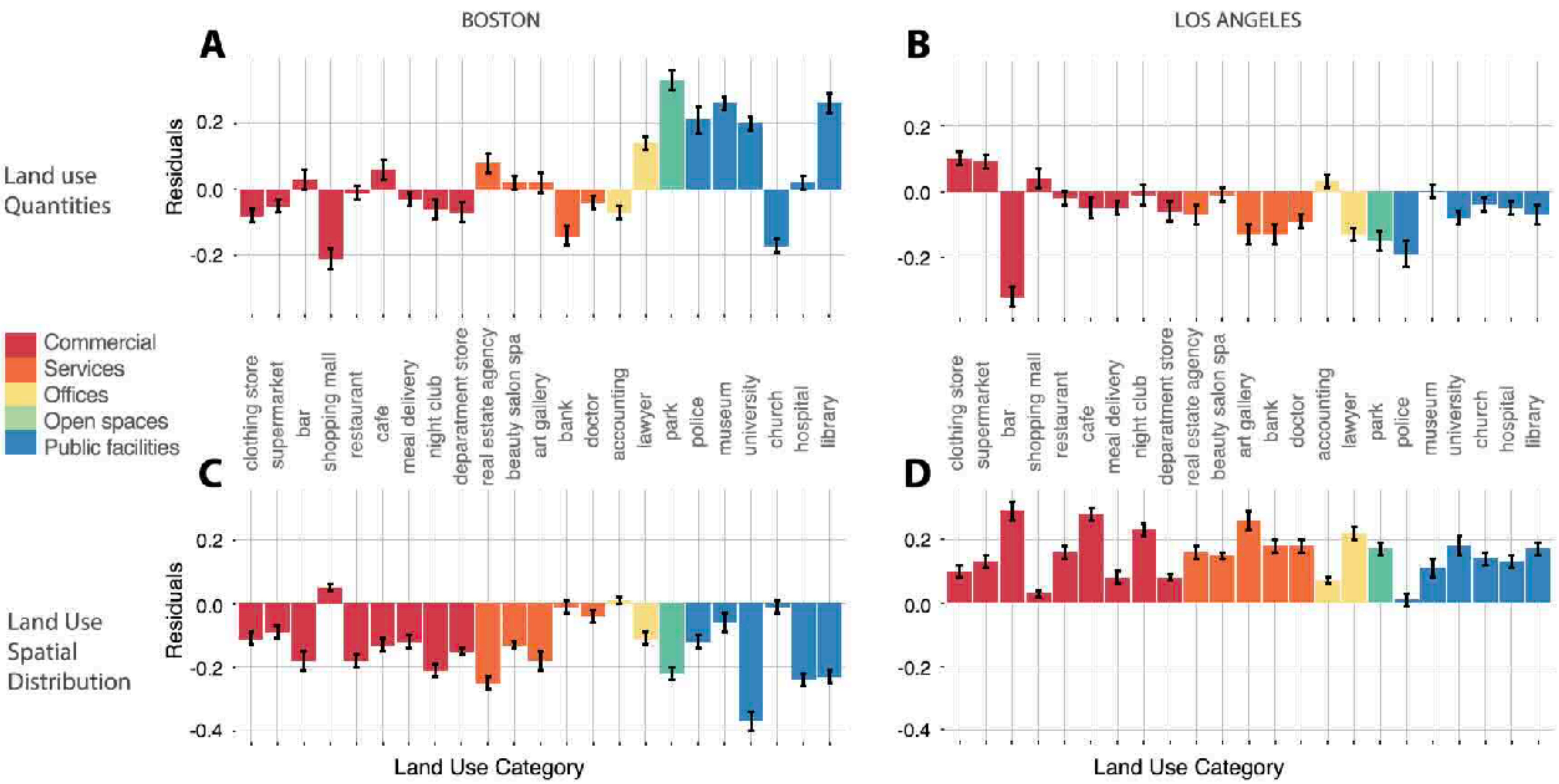


Figure 4 *Urban signatures*. The deviations from the regression line in double logarithmic scale are visualized as bars with the height of the bar being the value of the residual. Each color represents a different group of amenity types. We selected 23 representative categories from the amenity types that show a good fit with the population. (**A**), (**B**) Deviations from the expected quantity of amenities. Boston exceeds the expected quantities of most public facilities (e.g., libraries and museums) and open spaces while Los Angeles shows negative deviations in most amenity types. (**C**), (**D**) Deviations from the expected spatial distribution. Most amenities in Boston are more evenly distributed than expected, whereas in Los Angeles, most amenities are scattered around the city

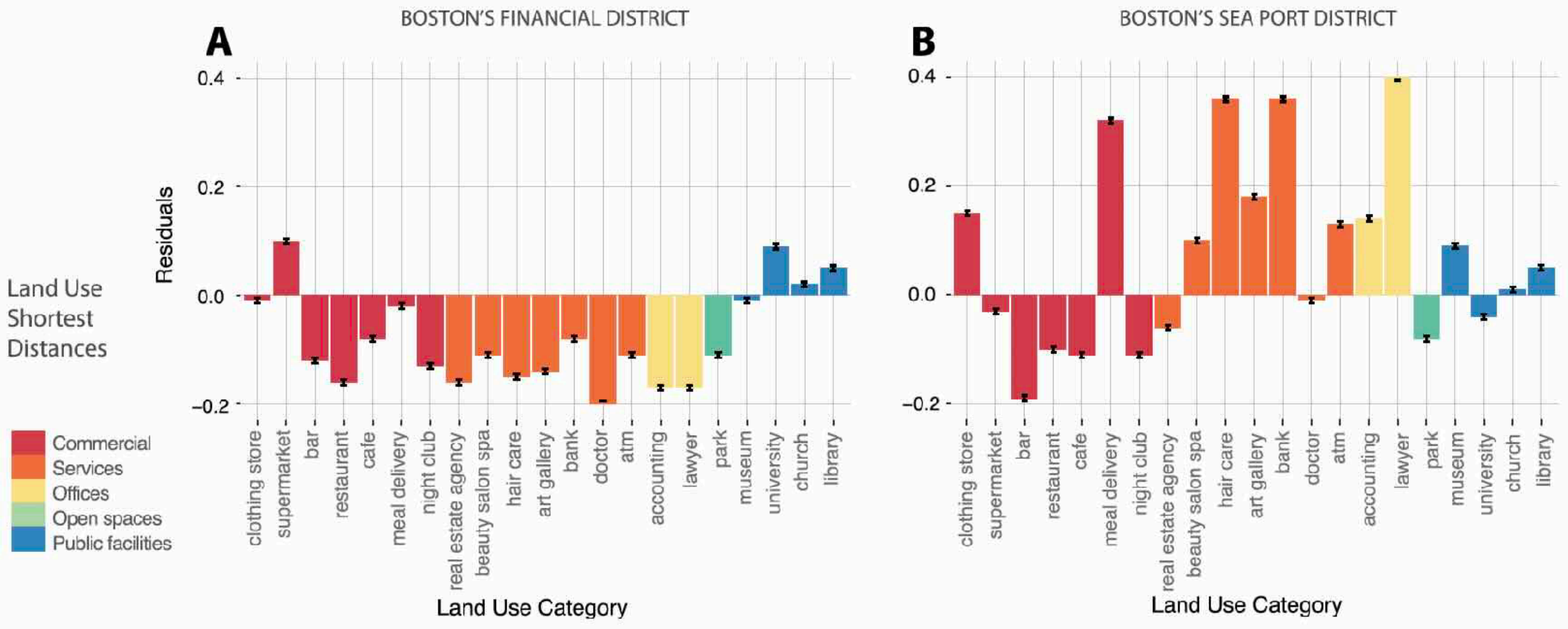


Figure 6 *Deviations from expected distance between amenities*. (**A**) In Boston's financial district, for most of the amenity types the mean shortest distance is shorter than one would expect given the density of amenities. (**B**) On the contrary, in Boston's seaport district, many amenity types are farther than one would expect

Comparative studies of cities and districts can be made quantitative and statistical

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