Urbanization in China: Discussion of Chauvin, Glaeser, Ma, Tobio (2017)

Nathan Schiff
Shanghai University of Finance and Economics

Graduate Urban Economics, Week 1
February 26th, 2024

Tentative Schedule

Important to start thinking about potential research ideas as soon as possible.

Inspiration: Beijing urban conference; spatial JMPs; 2024 US UEA; OSUS; NBER Urban papers

Schedule:

- 4th week: "Flash presentations." Students present research idea (5 minutes or less)
- 9th or 10th week: Midterm research outline
- End of term (or later): final proposal

Also, each student should present one supplementary paper at some point in the term. For each lecture I've provided a list of related papers, see "Student Presentations: Guidelines and Paper List" on website. Students are also welcome to choose their own paper, just get approval from me first.

JUE: Urbanization in Developing Countries

Special Issue (March 2017) emphasized that while in the past countries urbanized as they became wealthier, today countries with fairly low per-capita income still have high urbanization rates (China is a different case)

Given that much of urban economics theory and research is based on European and North American urbanization, important question is how well research applies to developing world (different income levels, different political structures, different era, and technology, of urbanization)

Published five papers on China looking at political favoritism in capital market, effect of high speed rail, housing demand, enforcement of building height restrictions, and general spatial patterns

Chauvin, Glaeser, Ma, Tobio, JUE 2017

Chauvin, Glaeser, Ma, Tobio (CGMT) note that most empirical work in urban economics has focused on the US

Urban empirical work in other countries beside US focused on developed countries (mostly Europe)

General question of CGMT: do all the spatial patterns documented in developed countries hold for developing nations?

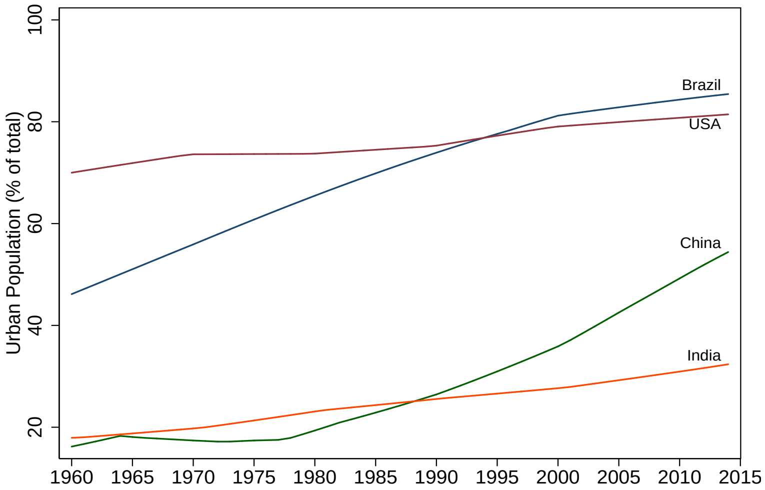
Examine US, Brazil, India, and China

Specifically look at 1) Zipf's Law 2) Spatial Equilibrium evidence 3) Agglomeration Externalities evidence

They do not look at *within* city patterns, focus of next couple classes

Urbanization in CGMT Countries

Figure 1: Share of total population living in urban areas, 1960-2014



Source: World Development Indicators, The World Bank.

What can we learn from this paper?

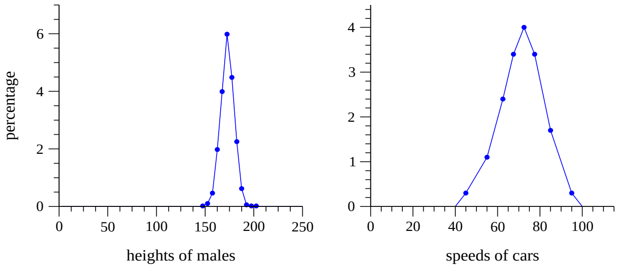
CGMT is a good paper for our class:

1. Good overall discussion of important empirical patterns in Urban Economics
2. Shows basic methods for documenting these patterns
3. Shows required data for China
4. Further, offers some evidence that China differs from US–possible ideas for future research

Zipf's Law and the City Size Distribution

Human Height and Automobile Speeds

Many natural and man-made quantities have a common value and fairly limited range. For example, the ratio of the tallest known man to the shortest man is about 4.8.

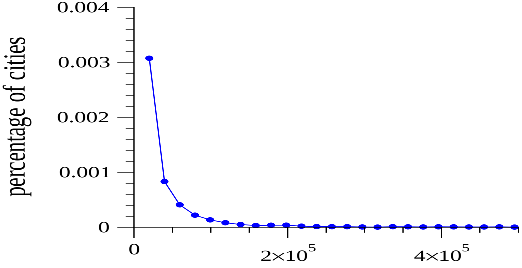


This example is from Newman, *Contemporary Physics*, 2005

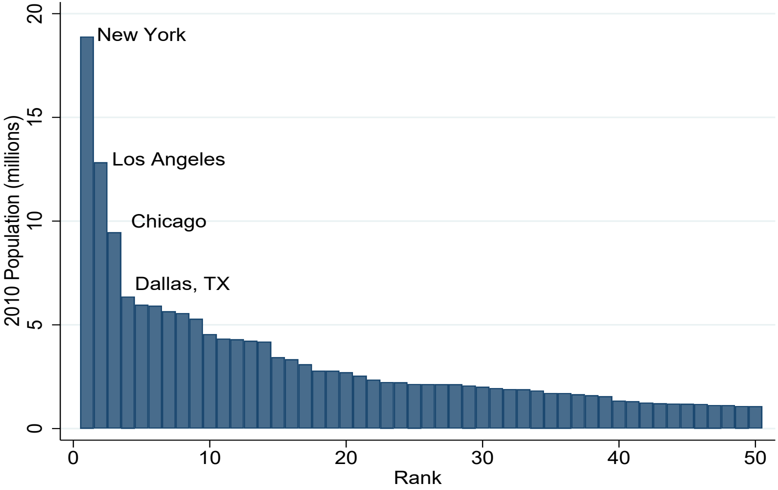
Range of City Sizes is Much Larger, Very Different Distribution

The largest city in China is Shanghai (24m) and there are many small cities under 100,000 (ratio of 240); there are also small villages and towns of 10,000 people, which are 2400 times smaller than Shanghai

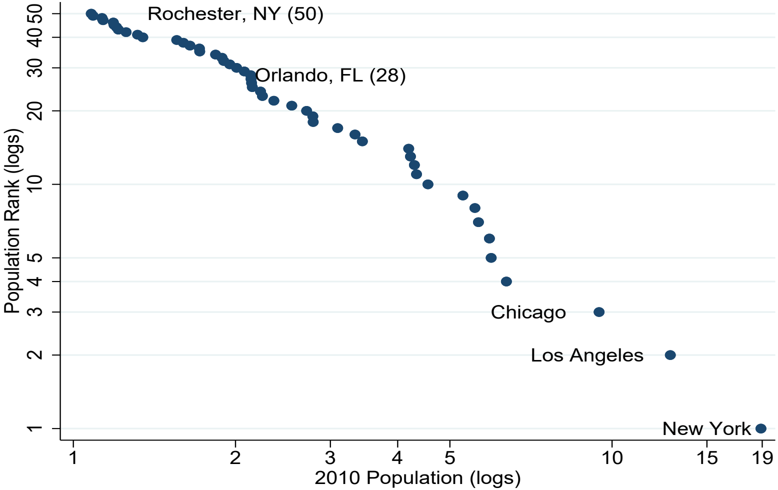
The largest city in the US is New York (19m). There are many places with fewer than 10,000 people and even towns with less than 1000 people. Thus the ratio of biggest to smallest is at least 19,000.



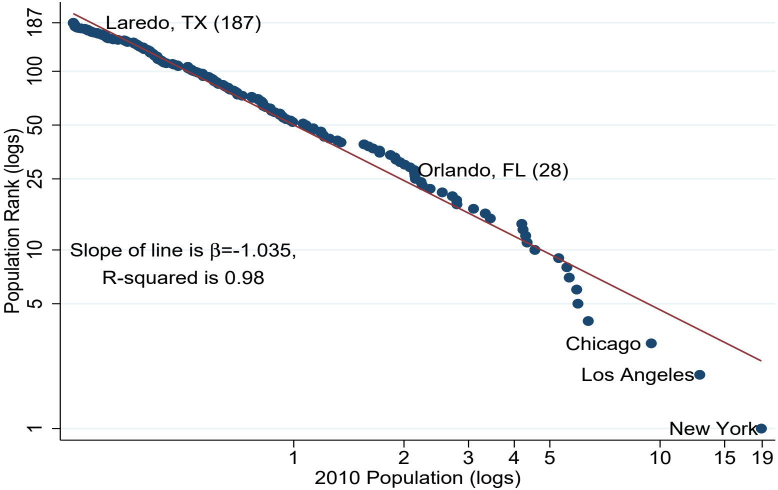
Bar Plot with 50 Largest US Metros, 2010



City Rank vs Population, Top 50, Logarithmic Scales



City Rank vs Population, Cities over 250k, Logarithmic Scales



A Remarkable Fit! What is going on?

While the largest cities were off the line, this is generally a remarkable fit!

In economics, we *never* have R-squared values of 0.98 (if you find one, you have made a mistake).

This fit implies that if we know only the rank of the city, we can make a very accurate prediction for the population (outside of the top 7 cities)

Further, we found $In(Rank) = \alpha + -1.035 * In(Population)$

Exponentiate both sides: $Rank = e^{\alpha} * Pop^{-1.035}$, or $Pop \approx e^{\alpha}/R$

This implies that the population of every city is proportional to its rank. The population of the largest city is $e^{\alpha}/1$, the second largest city is $e^{\alpha}/2$, third is $e^{\alpha}/3$.

Alternatively, the population of the second largest city is half the population of the largest, the pop of the third is a third the population of the largest, the population of the Nth city is $1/N$ times the population of the largest...**What is going on?**

Power Laws

Let $p(x)$ be the probability of observing a variable with a value equal to x, such as a height of 163cm ($x = 163$), or a city size of one million people ($x = 1000000$)

If this probability takes the form $p(x) = C * x^{-(\zeta+1)}$ then the distribution of this variable follows a *power law*.

The C term is just a constant and not important; the key term is ζ, with $\zeta \geq 0$. Since this exponent is negative, larger values of x are less likely to be observed.

$$Pr(X \geq x) = \frac{C}{\zeta} x^{-\zeta} = a * x^{-\zeta} \tag{1}$$

If observation x_r is the r largest observation (rank), then $Pr(X \geq x_r) \sim r$

Thus $r \sim ax^{-\zeta}$, or our plot: $ln(Rank) = ln(a) - \zeta * ln(Population)$

Power Laws

Let $p(x)$ be the probability of observing a variable with a value equal to x, such as a height of 163cm ($x = 163$), or a city size of one million people ($x = 1000000$)

If this probability takes the form $p(x) = C * x^{-(\zeta+1)}$ then the distribution of this variable follows a *power law*.

The C term is just a constant and not important; the key term is ζ, with $\zeta \geq 0$. Since this exponent is negative, larger values of x are less likely to be observed.

$$Pr(X \geq x) = \frac{C}{\zeta} x^{-\zeta} = a * x^{-\zeta} \quad (1)$$

If observation x_r is the r largest observation (rank), then $Pr(X \geq x_r) \sim r$

Thus $r \sim ax^{-\zeta}$, or our plot: $ln(Rank) = ln(a) - \zeta * ln(Population)$

1. C is unimportant in the sense that it is determined from the requirement that the probability must sum to 1: $\int_{x_{min}}^{\infty} p(x)dx = 1$. Given that the range goes to ∞, we must assume $\zeta > 0$, which yields $C = (\zeta)x_{min}^{\zeta}$, see Appendix A in Newman.
2. $Pr(X \geq x) = C \int_{s=x}^{\infty} s^{-(\zeta+1)} ds = \frac{C}{\zeta} x^{-\zeta}$
3. Consider drawing from a set of 100 observations. The probability of drawing a value $\geq$ to the largest value is 1/100. The probability of getting a value $\geq$ to the second largest value is 2/100, and so on.

Variables that Follow Power Laws are *Scale Free*

The probability of observing a variable with a value equal to x is:
$p(x) = C * x^{-(\zeta+1)}$

How much more likely are we to observe x compared to $2x$?

$$\frac{p(x)}{p(2x)} = \frac{C{*}x^{-(\zeta+1)}}{C{*}(2x)^{-(\zeta+1)}} = (1/2)^{-(\zeta+1)}$$

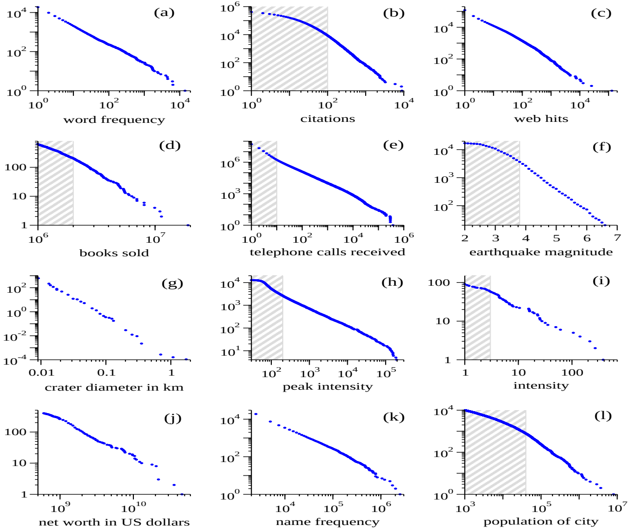
How much more likely are we to observe $1000x$ compared to $2000x$?

$$\frac{p(1000x)}{p(2000x)} = \frac{C{*}(1000x)^{-(\zeta+1)}}{C{*}(2000x)^{-(\zeta+1)}} = (1/2)^{-(\zeta+1)}$$

This is a very unique and unusual property. Say cities with 1000 people are four times more common than cities with 2000 people. Then it is also true that cities of one million people are four times more common than cities of two million people.

When a variable follows a power law, we see the same pattern at very small scales as we do at very large scales

Power Laws Examples: Newman, *Contemporary Physics*, 2005



Zipf's Law for Cities

When variables with power law distributions have a power of $\zeta = 1$ in the rank equation, $Rank \sim C * x^{-\zeta}$, we say the variable follows "Zipf's Law"

Zipf was a linguist who noticed that the frequency of any word in a language is proportional to its rank. For example, "the" is the most frequent word in English and is twice as common as the second most frequent word, "of"

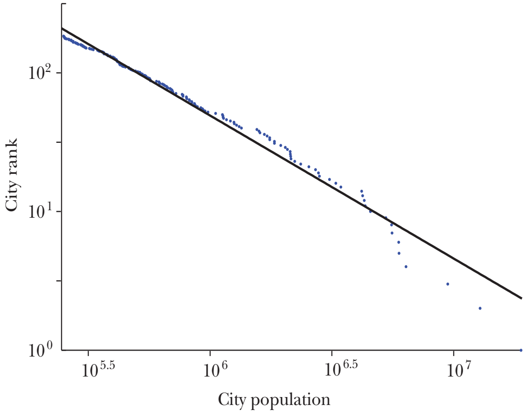
Zipf's Law for Cities is simply the statement that the city size distribution seems to follow a power law with an exponent of (negative) one (Gabaix 1999)

That is, $Rank = \frac{a}{Pop}$, or in logs $ln(Rank) = ln(a) - ln(Pop)$

But so far we have only seen evidence from the US; does Zipf's Law hold for cities in other countries? Does it hold for small cities as well as large cities?

Zipf's Law in US: Gabaix 2016

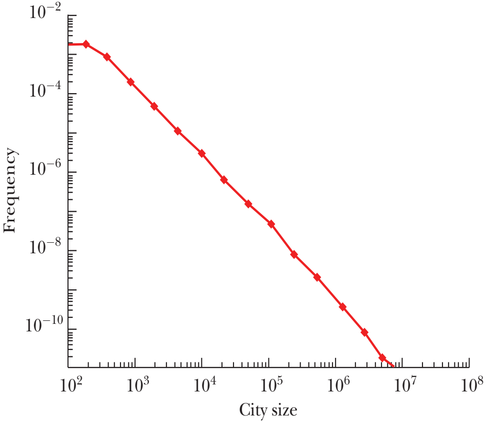
A Plot of City Rank versus Size for all US Cities with Population over 250,000 in 2010



Source: Author, using data from the *Statistical Abstract of the United States* (2012).
Notes: The dots plot the empirical data. The line is a power law fit ($R^2 = 0.98$), regressing ln *Rank* on ln *Size*. The slope is -1.03, close to the ideal Zipf's law, which would have a slope of -1.

Zipf's Law in UK: Gabaix 2016

Density Function of City Sizes (Agglomerations) for the United Kingdom



Source: Rozenfeld et al. (2011).
Notes: We see a pretty good power law fit starting at about 500 inhabitants. The Pareto exponent is actually statistically non-different from 1 for size $S > 12{,}000$ inhabitants.

Why is this important?

This empirical relationship is so strong $R^2 \sim 1$ some economists (Gabaix) propose that any system of cities model which tries to explain the data must lead to this regularity

For example, one of the classic models for cities (Henderson, 1974) does not lead to Zipf's distributions

Gabaix JEP 2016 considers this one of the few "non-trivial and true" results of economics

Note: this paper also discusses other power laws in economics and shows that firm size distribution is Zipf ($\zeta = 1$)

What explains Zipf's Law?

Say we start out with a set of cities of all different population sizes (some big, some small, etc...)

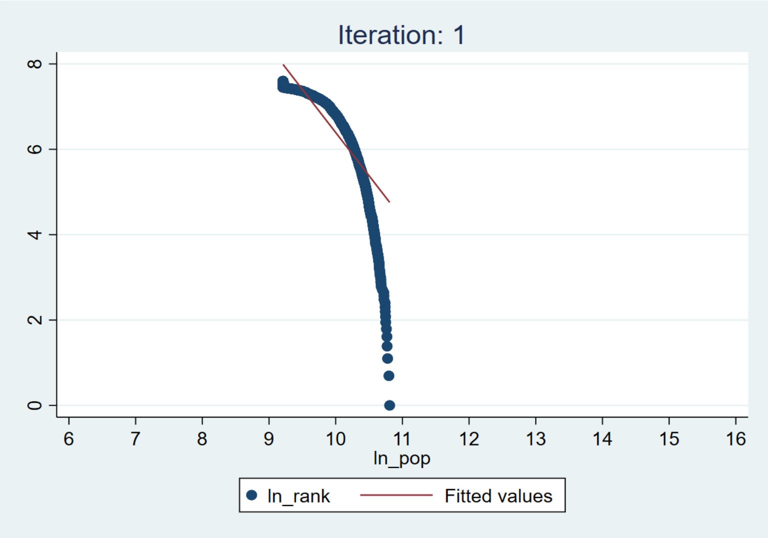
If these cities grow and shrink randomly—the population growth rate does not depend on the initial population size population level—then the distribution will converge to a power law

Technical note: there must also be a lower bound—cities cannot shrink below some fixed population

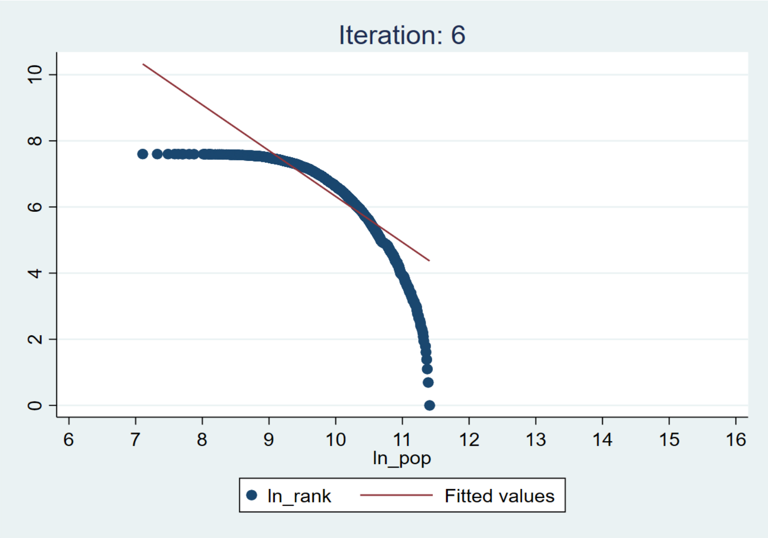
This exponent of this power law depends on the growth process, *but*, Gabaix (1999) showed that if the total population is fixed the exponent will converge to 1: Zipf's Law

Here is a simulation demonstration

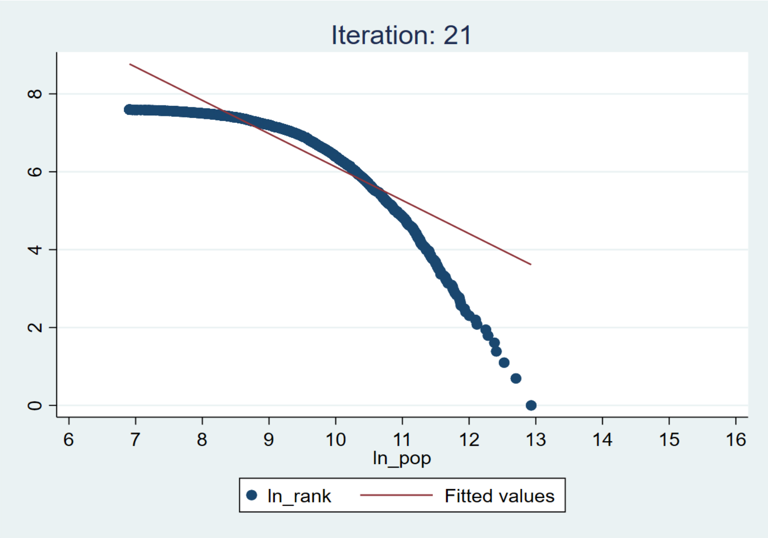
Random Growth Demonstration



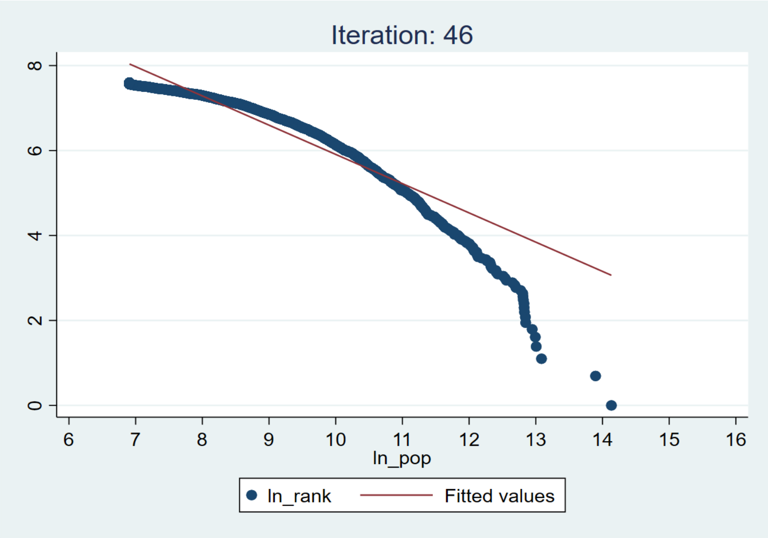
Random Growth Demonstration



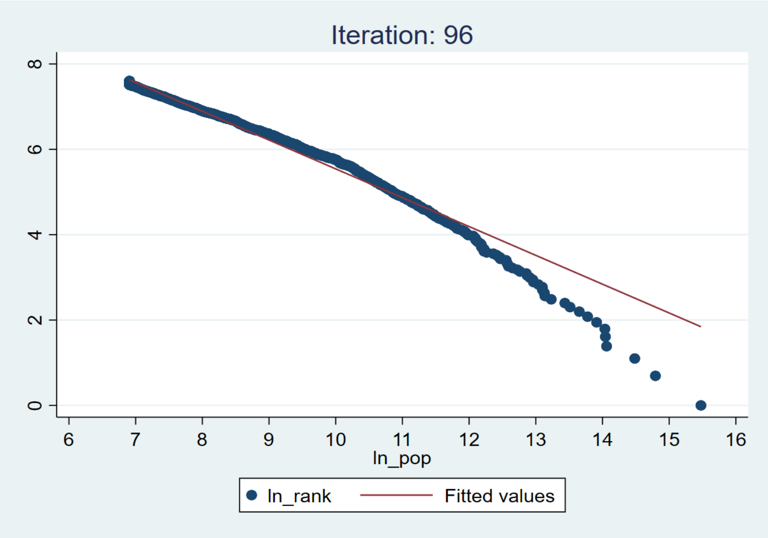
Random Growth Demonstration



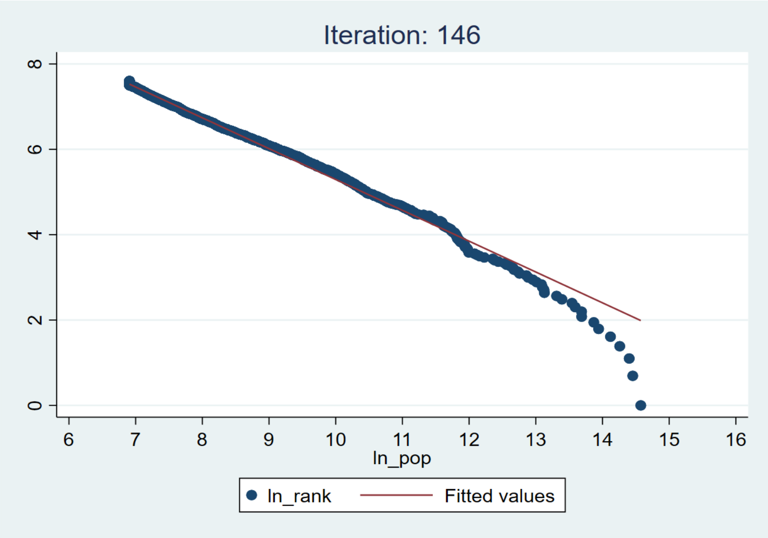
Random Growth Demonstration



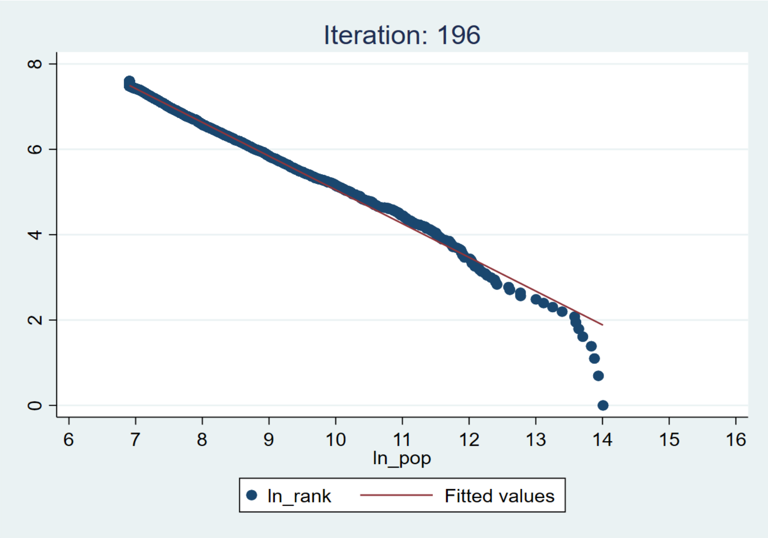
Random Growth Demonstration



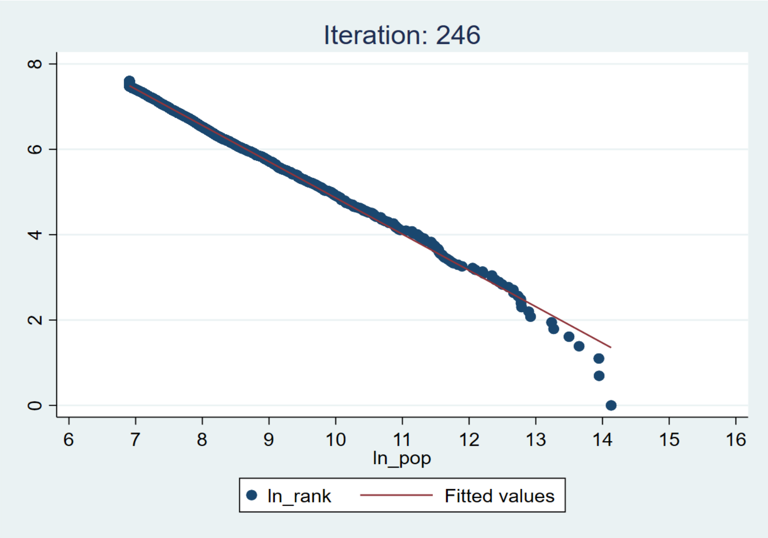
Random Growth Demonstration



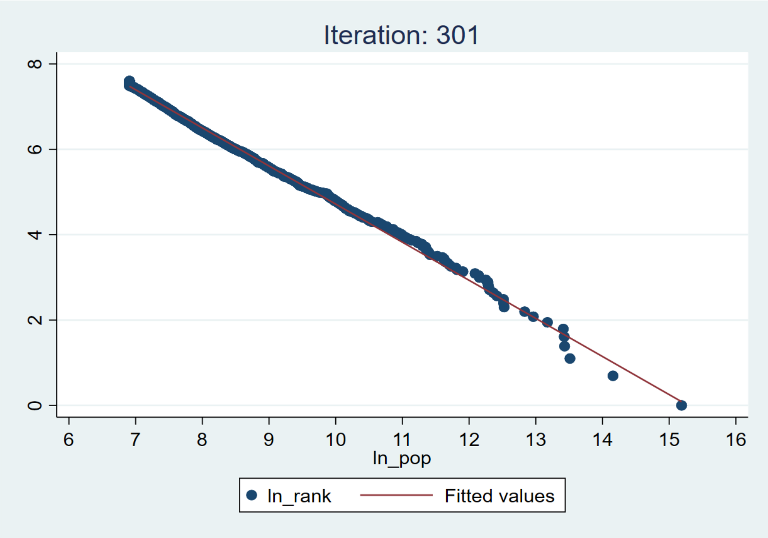
Random Growth Demonstration



Random Growth Demonstration



Random Growth Demonstration



Why Would Cities Grow Randomly?

Random growth is consistent with constant returns to scale: doubling inputs (ex: population) leads to double outputs, growth rate is same across cities of different sizes

But, lots of theories suggest city growth is affected by characteristics of the city (human capital levels, geography, amenities)

Further, empirical evidence suggests US cities with higher human capital have grown faster (Glaeser et. al. 1995, Shapiro 2006); we will see that effect seems to be very strong in China (Chauvin et. al. 2017)

This evidence seems to contradict random growth, although it's possible human capital effects eventually mean revert

There are also other models that can generate a Zipf distribution; see Behrens, Duranton, Robert-Nicoud (2013) for one example

Ongoing Line of Research

Zipf's Law continues to be extensively studied

Some discussion over exact form (power law vs log normal distribution, see Eeckhout 2004)

Much work on cross-country comparisons, including this paper

Additional work on how to define a city (Rozenfeld, Rybski, Gabaix, Makse, AER 2011)

How universal is Zipf's Law–does it hold among small geographies? (Holmes and Lee, 2010)

Lee and Li (JUE 2013) show that Zipf's Law can result from product of multiple random factors

Implies that cannot use Zipf's Law to test system of cities models since even if a single model does not yield Zipf's Law it may when combined with other models (and we do not usually assume our models are exhaustive)

Back to CGMT: Zipf's Law

CGMT look for evidence of Zipf's Law and Gibrat's Law in country sample

Focus is on simplest methodologies and use of data comparable across countries

Test Zipf's Law with standard regression of log(Rank) on log(Pop)—for econometric reasons they use log(Rank-0.5)

Test Gibrat's Law by regressing population growth on initial population

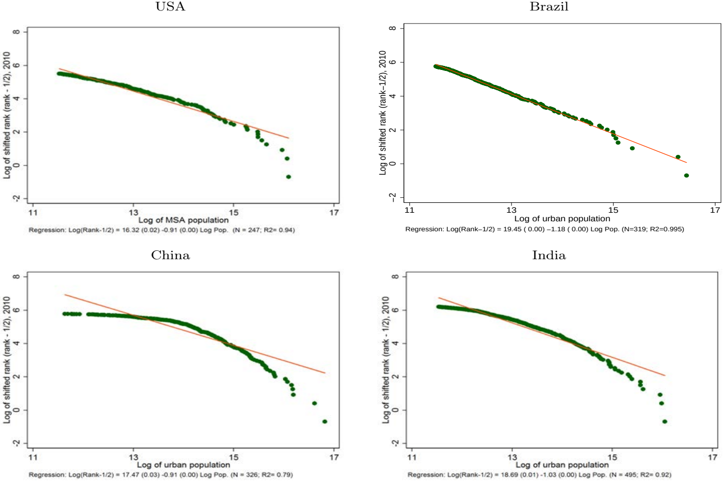
Back to CGMT: Zipf's Law

- CGMT look for evidence of Zipf's Law and Gibrat's Law in country sample
- Focus is on simplest methodologies and use of data comparable across countries
- Test Zipf's Law with standard regression of log(Rank) on log(Pop)—for econometric reasons they use log(Rank-0.5)
- Test Gibrat's Law by regressing population growth on initial population

1. If the equation is $y = ax^{-\zeta}$ then taking logs and regressing leads to a biased estimator of ζ. In Gabaix and Ibragimov 2011 they show that this bias is greatly reduced by simply subtracting 1/2 within the log function, $log(y - 0.5)$. This is still an approximation and not as accurate as estimating ζ with non-linear regression, but much simpler.

Zipf's Law, CGMT

Figure 2: Zipf's Law. Urban populations and urban population ranks, 2010



Note: Regression specifications and standard errors based on Gabaix and Ibragimov (2011). Samples restricted to areas with urban population of 100,000 or larger.

Sources: See data appendix.

Zipf Law Results

US has coefficient close to -1, consistent with past findings

In Brazil, fit is linear but slope is -1.18–steeper than Zipf's Law

China has very non-linear shape–does not fit straight line power law pattern

China has too *few* large cities to be consistent with Zipf's Law

India is also somewhat curved but closer to US fit

Authors also do KS test on distributions, find China's distribution particularly distinct from other three countries

Gibrat's Law Regressions

Table 4: Gibrat's Law: Urban population growth and initial urban population

	USA (MSAs)	**Brazil (Microregions)**	**China (Cities)**	**India (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

Note: All figures reported correspond to area-level regressions of the log change in urban population on the log of initial urban populations in the specified period. Regression restricted to areas with urban population of 100,000 or more in 1980. Robust standard errors in parentheses.
*** p<0.01, ** p<0.05, * p<0.1
Sources: See data appendix.

Discussion of Zipf and Gibrat Results

US and Brazil fit well but India doesn't and China is large outlier

China data also not consistent with Gibrat's Law; shows mean reversion, smaller cities grow faster

Authors suggest China may still be far from steady state spatial equilibrium

Further suggest that government role in migration could alter market-based city distribution

- Note: China has active population management policies, including population caps as part of "master urban plans" (ex: Shanghai 25m in 2035), seems reasonable that these policies could lead to deviations from Gibrat's Law

Authors suggest that possible in long-run "China's urban populations will be much more skewed towards ultra large areas like Beijing and Shanghai."

Dingel, Miscio, and Davis, JUE 2020

In US and Europe, metropolitan areas (economically connected parts of cities) are defined with commuting flows

In China and India, these spatial definitions are not available and so researchers usually use administrative (politically defined) areas

Problem: administrative areas may not correspond to economic areas, leading to strange results in analysis. For ex, DDM point out that Foshan and Guangzhou are only 18 miles apart and connected by a subway, yet are still defined as separate prefectures.

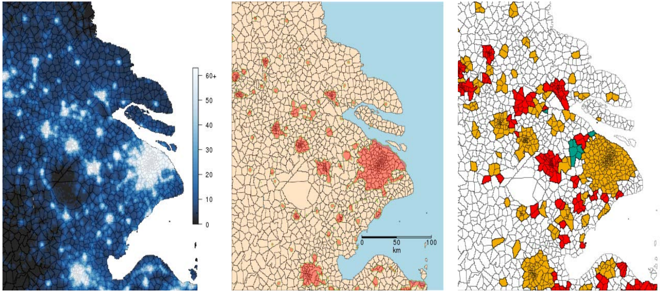
In "Cities, Lights, and Skills in Developing Economies," authors redo rank/size regressions (and additional analysis) using spatial units defined by satellite data on night lights intensity

With their definition of metro areas, Chinese cities conform to a power law (but with a coefficient greater than one)

Using night lights to defined metropolitan areas in China

Figure 1: Building metropolitan areas by aggregating smaller units based on lights at night

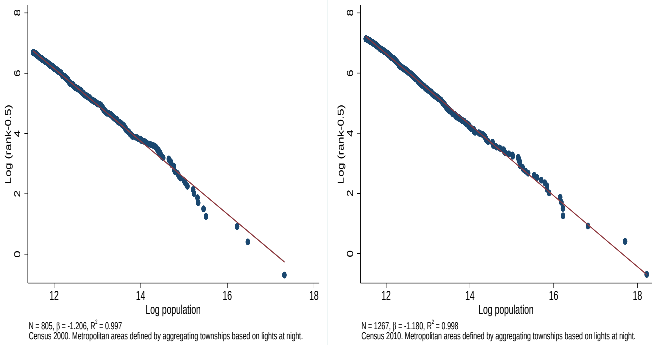
(a) Inputs (b) Forming polygons (c) Metropolitan areas



NOTES: This figure illustrates our procedure for combining satellite imagery of lights at night with administrative spatial units to build metropolitan areas. These panels depict a portion of the eastern coast of China in 2000. The administrative spatial units are townships. The polygons in the middle panel are areas of contiguous light brighter than 30. Aggregating the townships that intersect these polygons produces the metropolitan areas depicted in the right panel. Adjacent townships are often assigned to distinct metropolitan areas.

Zipf's Law for China using Metros defined with night lights

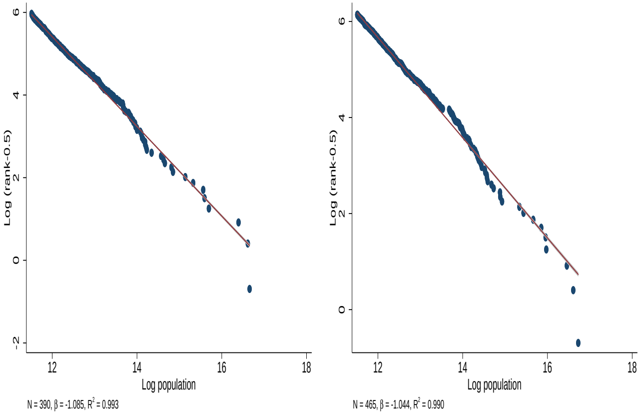
Figure 7: China's city-size distribution with night-lights–based units, 2000 and 2010



NOTES: The sample is Chinese metropolitan areas with population greater than 100,000. Metropolitan areas defined by aggregating townships in areas of contiguous night lights with intensity greater than 30. Left panel depicts 2000; right panel 2010.

Zipf's Law for India using Metros defined with night lights

Figure 8: India's city-size distribution, urban agglomerations, 2001 and 2011



Spatial Equilibrium

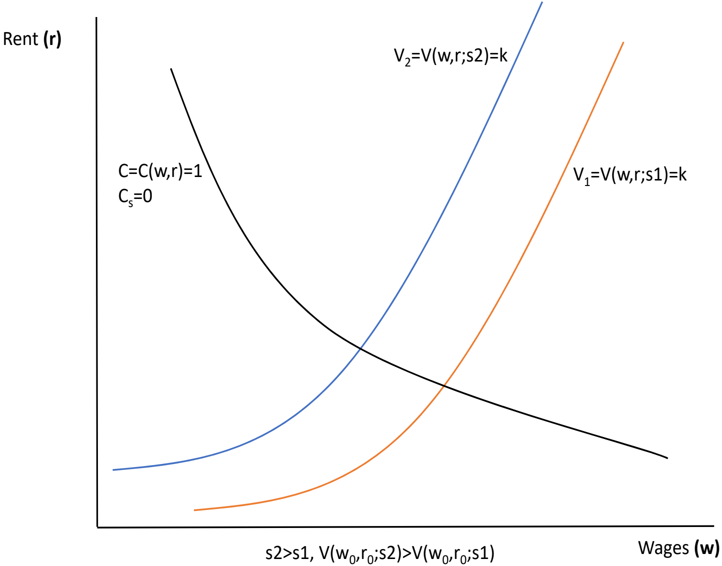
Testing Spatial Equilibrium Hypothesis

Spatial equilibrium hypothesis: migration causes wages and local prices to adjust across locations so that workers of same ability have equal utility in all locations (no spatial arbitrage in equilibrium)

CGMT test this idea by asking:

1. Do costs of living rise with wages?
2. Are real wages (wages - housing costs) lower in places with better climates (amenities)?
3. Is *happiness* constant across locations, consistent with equalization of utility?
4. How much within-migration is in each country?

Rosen-Roback Model: Consumer Amenity Only



s2>s1, $V(w_0,r_0;s2)>V(w_0,r_0;s1)$

Prices and Wages: Cobb-Douglas

Say people have utility $U = A * H^{\alpha} C^{1-\alpha}$ and after-tax wages $(1-t) * W$

Then indirect utility function, with constant K, is $V = K * A * (1-t)W * P_H^{-\alpha}$

Take logs and re-arrange: $ln(P_H) = \frac{1}{\alpha}(ln(K/V) + ln((1-t) * W) + ln(A))$, or:

$$Log(HPrice_i) = \frac{1}{\alpha}(Constant + Log(Wage_i) + Log(Amenities_i)) \qquad (1)$$

Then $\partial E[Log(HPrice_i)|X]/\partial Log(Wage_i) = \frac{1}{\alpha}\left(1 + \frac{Cov(Log(wage), Log(Amenities))}{Var(Log(Wage))}\right)$

If $Cov(Log(wage), Log(Amenities)) = 0$ then coeff=$1/\alpha$; US households spend $\alpha = 1/3$ of income on housing so coeff=3 (China's $\alpha = 1/10$)

Prices and Wages: Linear Form

Alternatively, assume perfectly inelastic housing demand with each person consuming H=1

Then numeraire consumption is $C = (1-t)W - P_H + A$, where A is additive for convenience

Then we have $P_H = (1-t)W + A - C$, or:

$$HPrice_i = AfterTxW_i + Amenities_i \tag{2}$$

Then $\partial E[HPrice_i|Wage_i]/\partial Wage_i = 1 - t + \frac{Cov(Wage, Amenities)}{Var(Wage)}$

If $Cov(Wage, Amenities) = 0$ then coeff=$1 - t$

Wages and Rents Regressions

Table 5

Regressions of local prices on wages, 2010.

	USA (MSAs)	Brazil (Microregions)	China (Cities)	India (Districts)	USA (MSAs)	China (Cities)
		Log of 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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Sources: See data appendix.

Wages and Rents Regressions

Table 5
Regressions of local prices on wages, 2010.

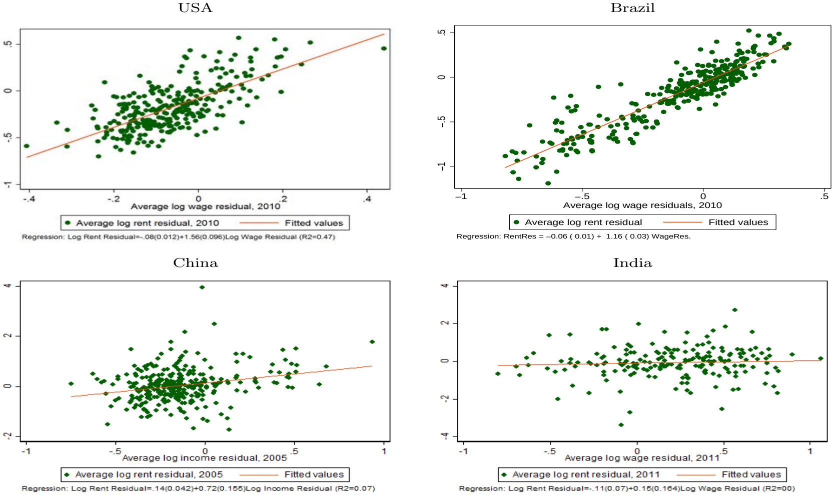
	USA (MSAs)	Brazil (Microregions)	China (Cities)	India (Districts)	USA (MSAs)	China (Cities)
	Log of rents				Log of prices	
Average log wage	1.225***	1.011***	0.853***	−0.044	1.922***	1.122 ***
	(0.106)	(0.044)	(0.157)	(0.052)	(0.172)	(0.073)
	N = 29 M	N = 819 K	N = 6.5 K	N = 1484	N = 56 M	N = 24.5 K
	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. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Sources: See data appendix.

1. p9: “The first row shows results when we define income as the average of the logarithm of income in the area. The second row instead uses the average of the residual from a regression of the logarithm of wages on human capital characteristics.”
2. NS: Note that authors clustered standard errors at area level, thus 29 million is not relevant observation count.

Wages and Rents Plots

Figure 3: Income and rents, 2010



Note: Samples restricted to areas with urban population of 100,000 or more.
Sources: See data appendix.

Discussion of Wages and Rents

Coeff in US is far below 3; suggests $Cov(Wages, Amenities) < 0$, rent data is poor measure of housing costs, or unobserved human capital much higher in high wage cities–why?

Spatial equilibrium only holds for workers of same skill level–more productive workers should earn higher wages compared to less productive workers in same location

Fit for China much worse ($R^2 = 0.07$), coeff about 1, why?

CGMT list possibilities: 1) strong negative correlation between wages and amenities 2) hukou system 3) differences in housing market counteract equilibrium effects (small rental market, significant government intervention in housing policy)

From personal experience, 0.1 housing expenditure share difficult to believe

Real Wages and Amenities

Areas with positive amenities should have lower real wages (nominal wage/house price), why?

CGMT uses January+July temperature and rainfall to measure amenities

Regress $ln(W_i) - ln(PH_i)$ or $W_i - PH_i$ on these weather amenities

Real Wages and Amenities: US, Brazil

Table 6: Climate amenities regressions, 2010

	USA (MSAs)			Brazil (Microregions)		
	Log wage	**Log real wage**	**Log rent**	**Log wage**	**Log real wage**	**Log rent**
Absolute difference from ideal temperature in the summer (Celsius)	0.001	0.006***	-0.027***	-0.077***	-0.042***	-0.095***
	(0.003)	(0.001)	(0.008)	(0.006)	(0.003)	(0.010)
Absolute difference from ideal temperature in the winter (Celsius)	0.002	0.005***	-0.018***	-0.015**	-0.005	-0.016
	(0.002)	(0.001)	(0.003)	(0.006)	(0.004)	(0.012)
Average annual rainfall (mm/month)	0.000	0.000	0.000**	0.002***	0.000	0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Education groups controls	Y	Y	N	Y	Y	N
Age groups controls	Y	Y	N	Y	Y	N
Dwelling characteristics controls	N	N	Y	N	N	Y
Observations (thousands)	28,237	8,497	24,125	2,172	2,172	819
Adjusted R-squared	0.249	0.158	0.117	0.340	0.317	0.480

Real Wages and Amenities: China, India

	China (Cities)			India (Districts)		
	Log wage	**Log real wage**	**Log rent**	**Log wage**	**Log real wage**	**Log rent**
Absolute difference from ideal temperature in the summer (Celsius)	-0.005	-0.006	-0.001	0.000	-0.004	0.001
	(0.018)	(0.015)	(0.021)	(0.004)	(0.006)	(0.001)
Absolute difference from ideal temperature in the winter (Celsius)	0.003	-0.004	0.019**	-0.001	0.003	0.000
	(0.009)	(0.009)	(0.009)	(0.003)	(0.004)	(0.001)
Average annual rainfall (mm/month)	0.000	0.000	0.001***	0.000**	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Education groups controls	Y	Y	N	Y	Y	N
Age groups controls	Y	Y	N	Y	Y	N
Dwelling characteristics controls	N	N	Y	N	N	Y
Observations (thousands)	5.8	4.2	3.4	8.4	1.8	2.9
Adjusted R-squared	0.145	0.118	0.079	0.235	0.228	0.762

Note: Regressions at the individual level, restricted to urban prime-age males or urban household level (renters only) in areas with urban population of 100,000 or more. All regressions include a constant.

Discussion: Real Wages and Amenities

In US, real wages are higher where climate is worse, consistent with high amenities low real wage idea

Authors argue this is due to low rents in places with less attractive climates (column 3); find no effect on nominal wage

China and India show no relationship–any ideas why?

Using Happiness to Evaluate Equal Utility

If equal utility holds then happiness should be (roughly) equal across regions

- Possible that happiness is a proxy for amenities: if so, real income should be *lower* in places where people are happier.

Authors note that interpreting happiness differences across locations is difficult: heterogeneity could be due to heterogeneity in sampled individuals (ex: different ethnic groups or sorting)

Instead they check if happiness changes with income; spatial equilibrium says should be no relationship–why?

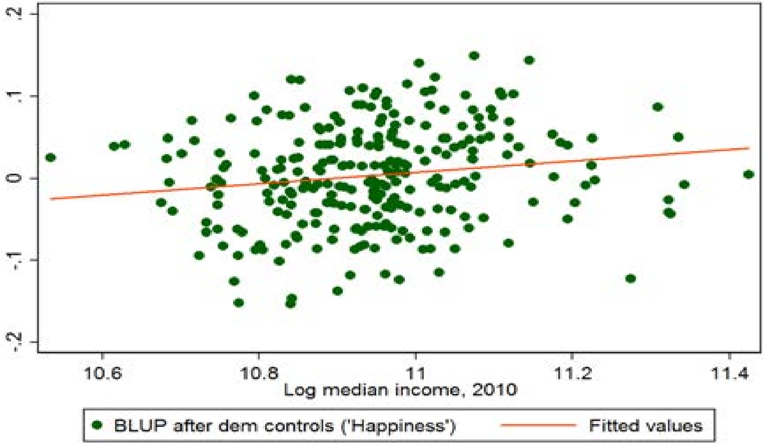
Find that US has slight positive coefficient (happiness on income); China has large positive coefficient, just barely significant

Speculate China relationship due to either 1) unobserved human capital higher in richer places 2) happiness reflects amenities 3) spatial equilibrium doesn't hold due to migration barriers (ex: hukou)

Happiness and Wages: US

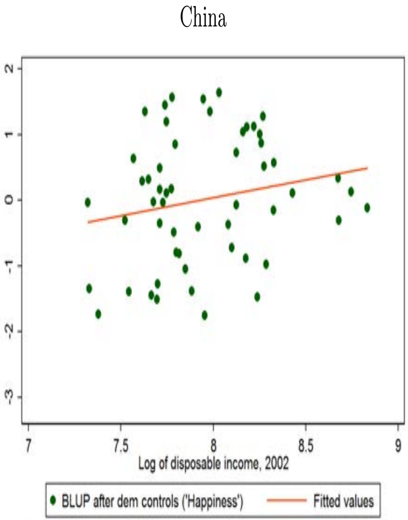
Figure 4: Happiness and income levels

USA

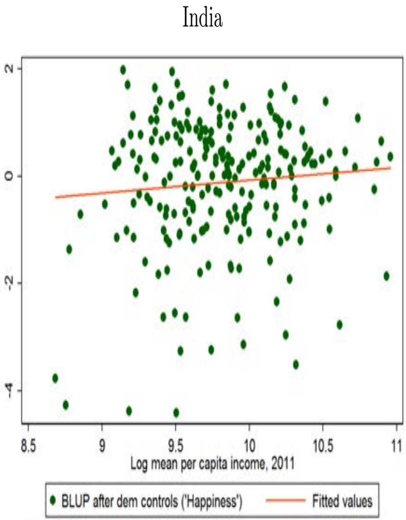


Regression: Happiness=-.76(0.292)+0.07(0.027)Log Median Income (R2=.03)

Happiness and Wages: China, India



Regression: Happiness=-4.3(02.972)+0.54(0.373)Log Disposable Income (R2=0.04)



Regression: Happiness=-2.44(01.73)+0.24(0.176)Log Mean Per Capita Income (R2=0.01)

Measuring Mobility

Spatial equilibrium model does not require people to move; housing prices can adjust to reach equilibrium

However, if there *is* limited mobility then spatial equilibrium may not hold

CGMT look at migration in 4 countries, find significant mobility in China

Use China Census data (county-level), look at “migrants in last 5 yrs”

Conclude that Chinese mobility comparable to US mobility, high enough to allow spatial equilibrium

Migration and Mobility

Table 7: Percentage of the population living in a different locality five years ago

	USA			Brazil		
	1990	**2000**	**2010**	**1991**	**2000**	**2010**
Migrants in the last 5 years (% of population)	**21.3%**	**21.0%**	**13.8%**	**9.5%**	**9.1%**	**7.1%**
From same state/prov., different county / dist.	9.7%	9.7%	6.7%	6.0%	5.4%	4.5%
From different state/province	9.4%	8.4%	5.6%	3.5%	3.6%	2.4%
From abroad	2.2%	2.9%	1.5%	0.04%	0.1%	0.14%
		China		**India**		
		2000	**2010**	**1993**	**2001**	**2011**
Migrants in the last 5 years (% of population)		**6.3%**	**12.8%**	**1.9%**	**2.6%**	**2.0%**
From same state/prov., different county / dist.		2.9%	6.4%	1.3%	1.5%	1.2%
From different state/province		3.4%	6.4%	0.6%	1.0%	0.8%
From abroad		N/A	N/A	0.02%	0.1%	0.03%

Sources: See data appendix.

Agglomeration and Human Capital in Cities

Productivity in Big Cities: Agglomeration Externalities

One of the most fundamental ideas in urban economics is that concentrating workers leads to higher productivity

Without such a force, the only way to explain the existence of cities is through heterogeneity in land productivity (very hard story to justify Beijing/Shanghai)

Extensive and deep empirical work in urban economics documents agglomeration externalities, simplest form regresses log wage on log population (Melo et. al. 2009 meta analysis suggests elasticity of 0.02-0.1)

Lots of recent work on agglomeration benefits of concentrating high skilled workers (ex: Moretti papers)

CGMT focus on 1) population (density) on wages 2) area education on wages and pop. and wage growth

Estimating Agglomeration Externalities in CGMT

Two issues with log(wage)∼log(pop) regressions: 1) unobserved productivity 2) sorting

Some cities may be more naturally productive, which causes in-migration and increases wages (omitted variable bias at city level)

It's also possible that unobservably skilled people sort into larger cities (see Card, Rothstein, Yi, 2023—a good paper for student presentation)

Difficult identification but usually addressed by instrumenting population with historical values and trying to control for sorting with education covariates

For sorting, can also compare estimates from nominal wages to real wages. If agglomeration is only due to sorting, then real wages should also be higher; if all people (all skills) receive same productivity benefit, then this should be offset by higher costs, leading to no effect in real wages.

Agglomeration Results (tables next)

US coefficients are much lower for real income than nominal income, suggesting at least half of agglomeration effects are not due to sorting

Agglomeration externalities appear to be higher in China than US; this pattern also found in other papers

Results are more precise when measuring city size with density, rather than population; CGMT suggest density is more accurate if a region actually includes multiple distinct cities

Real income regressions on density results also smaller for China

Note: presence of large number of migrants in big cities, who live in dorms and send money back home, seems like a factor that could affect basic model

Agglomeration Externalities: Nominal Income

Table 8: Income and agglomeration, 2010

	USA (MSAs)	Brazil (Microregions)	China (Cities)	India (Districts)
	Log wage	**Log wage**	**Log wage**	**Log wage**
OLS regressions				
Log of urban population	0.0538***	0.052***	0.0875	0.0770***
	(0.00720)	(0.013)	(0.0708)	(0.0264)
	R2=0.255	R2=0.321	R2=0.014	R2=0.251
Log of density	0.0457***	0.026**	0.192***	0.0760***
	(0.00865)	(0.010)	(0.0321)	(0.0195)
	R2=0.235	R2 = 0.318	R2=0.237	R2=0.257
Observations	28.5M	2,172 K	147K	9,778
IV1 regressions				
Log of urban population	0.0559***	0.051***	0.0320	0.160
	(0.00753)	(0.014)	(0.102)	(0.0998)
	R2=0.256	R2 = 0.321	R2=0.173	R2=0.237
Log of density	0.0431***	0.026**	0.169***	0.0828***
	(0.00888)	(0.011)	(0.0367)	(0.0218)
	R2=0.253	R2 = 0.318	R2=0.240	R2=0.253
Observations	28.5M	2,172 K	143K	7,627
IV2 regressions				
Log of urban population	0.0764***	0.015	0.320*	0.233**
	(0.0130)	(0.021)	(0.156)	(0.0963)
	R2=0.255	R2 = 0.315	R2=0.117	R2=0.224
Log of density	0.0493***	0.015	0.323***	0.0749***
	(0.0173)	(0.012)	(0.0847)	(0.0229)
	R2=0.253	R2 = 0.315	R2=0.242	R2=0.256
Observations	28.5M	1,998 K	112K	5,245
Educational attainment controls	Yes	Yes	Yes	Yes
Demographic controls	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.
Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Sources: See data appendix.

Agglomeration Externalities: Real Income

Table 9: Real income and agglomeration, 2010

	USA (MSAs)	Brazil (Microregions)	China (Cities)	India (Districts)
	Log real wage	Log real wage	Log real wage	Log real wage
OLS regressions				
Log of urban population	0.0190**	0.011	-0.0313	0.0688**
	(0.00916)	(0.010)	(0.0307)	(0.0298)
	R2= 0.067	R2=0.310	R=0.174	R2=0.240
Log of density	0.0219	0.002	0.0516**	0.0691***
	(0.0134)	(0.007)	(0.0166)	(0.0213)
	R2=0.068	R2=0.309	R2=0.179	R2=0.244
Observations	28.5M	2,172 K	147K	2,102
IV1 regressions				
Log of urban population	0.0209**	0.009	-0.0664	0.116
	(0.0102)	(0.010)	(0.0485)	(0.0927)
	R2=0.068	R2 = 0.310	R2=0.174	R2=0.243
Log of density	0.0230*	0.001	0.0345*	0.0647**
	(0.0134)	(0.007)	(0.0175)	(0.0255)
	R2=0.068	R2 = 0.309	R2=0.179	R2=0.241
Observations	28.5M	2,172 K	143K	1,649
IV2 regressions				
Log of urban population	0.0466**	-0.017	0.0648	0.208**
	(0.0190)	(0.016)	(0.0743)	(0.0840)
	R2=0.065	R2 = 0.305	R2=0.161	R2=0.244
Log of density	0.0419**	-0.008	0.0665	0.0512*
	(0.0163)	(0.008)	(0.0625)	(0.0263)
	R2=0.067	R2 = 0.307	R2=0.179	R2=0.241
Observations	28.5M	1,998 K	112K	1,141
Educational attainment controls	Yes	Yes	Yes	Yes
Demographic controls	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.
Robust standard errors in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
Sources: See data appendix.

Agglomeration and Human Capital Externalities

Authors discuss a series of regressions of *area* education and wages

Regress individual wage on indiv. characteristics and area education levels, instrumenting with predicted education levels (use age structure)

Notably, find very large return to human capital in China: "We believe...extremely high measured levels of human capital externalities especially in Brazil and China suggest that this is an important topic for future research." (see Glaeser and Lu 2018)

A ten percent increase in share of adults with college education in a city leads to sixty percent increase in earnings

Also examine effect of area education on urban growth: 1 percentage point increase in share of adults with college degrees in 1980 China is associated with 19 percentage points increase in population growth

Human Capital Externalities

Table 10: Human capital externalities, 2010

	USA (MSAs)		Brazil (Microregions)		China (Cities)		India (Districts)	
	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)	34M	27M	2,172 K	2,1712 K	147K	147K	12K	12K
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	27M	27M	2,172K	2,172 K	147K		11 K	11K
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)	17M	16M	2,172 K	2,172 K	147K		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

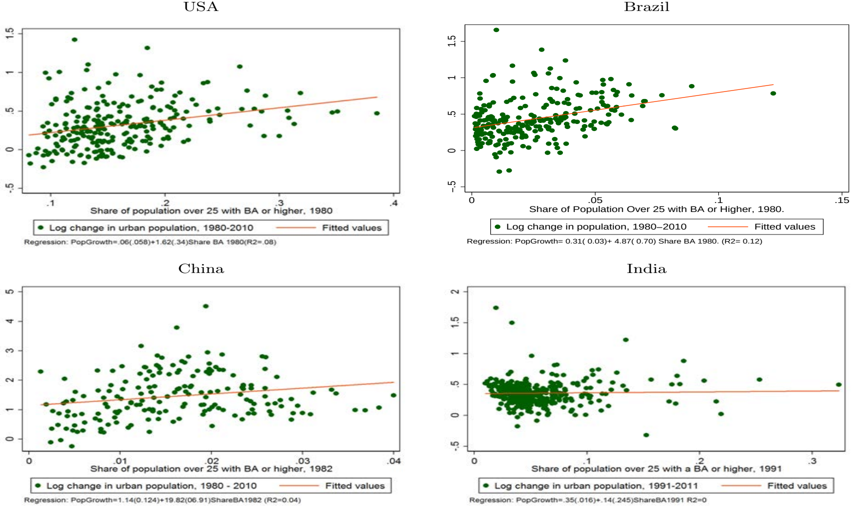
Note: Regressions at the individual level, restricted to urban prime-age males in areas with urban population of 100,000 or more. All regressions include a constant. Robust standard errors in parentheses.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Sources: See data appendix.

Education and Growth

Figure 5: University graduates share and population growth 1980-2010



Note: Samples restricted to areas with total population of 100,000 or more in 1980.

CGMT Concluding Thoughts

1. US and Brazil follow Zipf; China and India have too few large cities
2. Relationship between income and rents similar in US, Brazil, and China; not India
3. Generally, spatial equilibrium not as strong a fit in China as US and Brazil; authors suggest this might reflect hukou system
4. Connection between human capital and area success (growth) higher in Brazil, China, India compared to US
5. Overall, suggest spatial equilibrium model appropriate for Brazil, China, US, but not India

Supplementary Papers

1. Papers on Zipf's Law in China, including: Luckstead and Devadoss (Ec. Letters 2014), Soo (Papers in Regional Science 2014), or others (get my approval first)
2. Card, Rothstein, Yi, "Location, Location, Location," *Working Paper*, 2023, https://eml.berkeley.edu/ jrothst/workingpapers/Location_2023Aug.pdf
3. Combes, Demurger, Li, Wang, "Unequal Migration and Urbanisation Gains in China," *Journal of Development Economics*, 2020
4. Combes, Demurger, Li, "Migration Externalities in Chinese cities," *European Economic Review*, 2015
5. Dingel, Miscio, Davis, "Cities, Lights, and Skills in Developing Economies," *Journal of Urban Economics*, 2020
6. An, Qin, Wu, You, "The Local Labor Market Effects of Relaxing Internal Migration Restrictions: Evidence from China," *Journal of Labor Economics*, 2024