EC1410 Topic #2

The Monocentric City Model: Empirical evidence

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Outline

1. Review: Monocentric city model predictions
2. Cities in real life
3. Rent Gradients and COVID-19
4. Highways and decentralization
5. Highways and growth
6. Subways, decentralization and growth
7. Amenities and city size
8. Property taxes and land prices
9. Wages and rents
10. Conclusion/Summary

We've now developed the most basic version of the monocentric city model pretty thoroughly.

This model assumes: spatial equilibrium, costly commuting, central employment.

The model makes the following predictions.

- $R(x)$ decreasing in x. We've seen this is broadly consistent with observation.
- As commuting costs, t, decrease,
  - utility and consumption, $\overline{u}$, c^* constant(by assumption).
  - Rent gradient gets flatter, intercept stays the same.
  - City gets longer, $\overline{x} \uparrow$.
  - Population increases, $N \uparrow$.
  - A larger share of population lives outside any given distance from the center.
  - Aggregate rent goes up (and this measures welfare).

- As wages, w, increase,
  - utility and consumption, $\overline{u}$, c^* constant(by assumption).
  - Slope of rent gradient unchanged, intercept increases by Δw.
  - City gets longer, $\overline{x} \uparrow$.
  - Population increases, $N \uparrow$.
  - Aggregate rent goes up (and this measures welfare).
- As agricultural rent changes, what happens? Not done. No empirical results on this, so there's not really anything we can check.
- As amenities, A increase,
  - utility constant, but consumption c^{**} falls.
  - Slope of rent gradient unchanged, intercept increases.
  - City gets longer, $\overline{x} \uparrow$.
  - Population increases, $N \uparrow$.
  - Aggregate rent goes up (and this measures welfare).

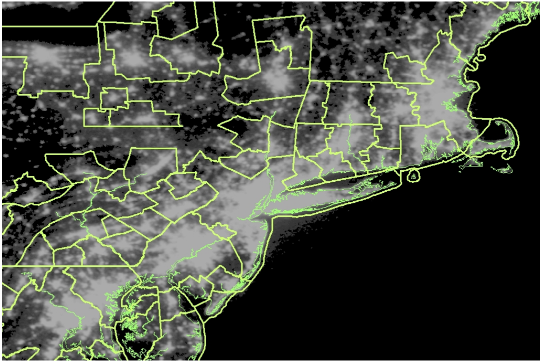
- Changes in property taxes do not change anything except how much rent is collected by absentee landlords. This is called the Henry George Theorem.

Aside – Defining ‘cities’ in real life I

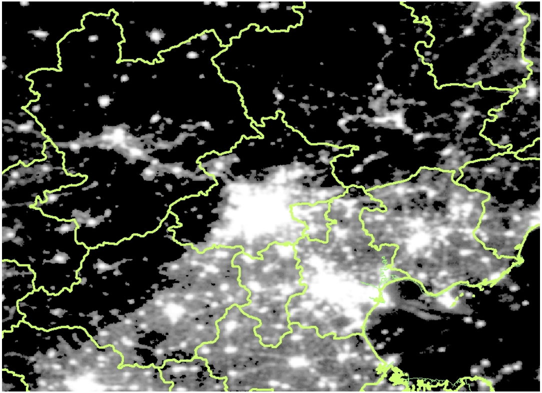
- We need some real group of people to try to match to our theoretical cities.
- If you think carefully about this, it’s pretty hard.
- I think we want something like a ‘labor market’. That is, an area in which all residents work and live.
- This is fussy. In the US, the main unit is a metropolitan statistical area, or MSA. Think of these as metropolitan areas of at least 50k built from counties. They are purely reporting units. There are a few different flavors, ‘micropolitan statistical areas’, CBSA’s, CMSAs. Definitions are easy to find on the census website.
- Many of the empirical papers we discuss will use this definition of ‘city’.

Aside – Defining ‘cities’ in real life II

- Other candidates are,
  - municipal boundaries: These are administrative boundaries and need not contain their CBD; consider any suburban municipality.
  - ‘Urbanized areas’, these are more about land use than about function. They are more narrowly about where people live and they tend to match pretty closely to remote sensing data showing the presence of buildings.
- Other countries typically keep track of pretty similar units, either based on administrative or reporting boundaries.



MSAs in New England, cs 2019 and lights at night ca 2013. The New York MSA is in the center of the picture.



Prefectural cities in China ca 2005. and lights at night ca 2013, Beijing is central. Prefectural cities are the nearest analog to US MSAs. But, prefectures are also administrative units in China, whereas, MSAs are purely reporting units in the US.

Rent Gradients and COVID-19 I

In the context of the monocentric city model, COVID-19 can be thought of as having two effects

- It reduces commuting costs. Most people commuted a lot less often, so on average, t should have decreased. This implies the rent gradient flattens, intercept unchanged, and the city gets longer and more populated.
- It decreases the amenity value of living close to the center. This is not quite the case we looked at (we had changes in amenities the same everywhere), but it is close. This is going to decrease the rent gradient everywhere, decrease the length and population of the city.

Rent Gradients and COVID-19 II

- Adding these two effects, we should have land rents flatten, and decrease at the center. The total effects on city extent and population are ambiguous.

Rent Gradients and COVID-19 III

- Gupta et al. (2021) look at how the housing market changed during the first year of COVID.
- To do this, they assemble lots of data describing real estate transactions and their distance from center of the city.
- For rental price and sales price they rely on Zillow price indexes available at the zipcode/month level.
- These are indexes that are supposed to describe the price or rent for a ‘standard’ house.

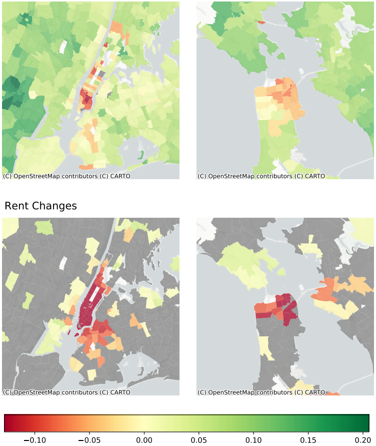


Figure 2. Price and Rent Growth, NYC and SF This map shows year-over-year changes in prices (top two panels) and rents (bottom two panels) for the New York and San Francisco MSAs at the ZIP code level over the period Dec 2019-Dec 2020. The bottom two rows zoom in on the city center. Darker green colors indicate larger increases, while darker red colors indicate larger decreases. From Gupta et al. (2021).

Density gradients, again

There is a long tradition of estimating gradients in urban economics. We have already seen land price gradients, and showed that

$$y = Ax^b \iff \ln y = lnA + b \ln x$$

To estimate such a gradient, researchers typically specify a regression equation

$$\ln y = lnA + b \ln x + \epsilon$$

for a single city.

Gupta et al. (2021) do this for before and after the pandemic, but they use the data for the 30 largest US metropolitan areas, to get a sort of average rent and price gradient.

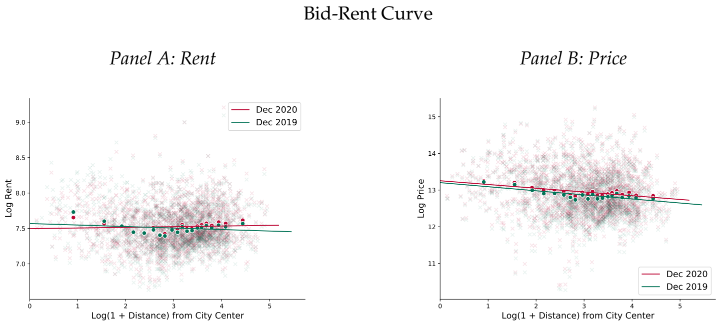


Figure 3. Pandemic Induced Changes in Prices and Rents The top two figures show the bid-rent function for the top 30 MSAs: the relationship between distance from the city center (the log of the distance in kilometers from City Hall) and the log of rents (Panel A) and prices (Panel B). Lighter points indicate ZIP codes, while darker points indicate averages by 5% distance bins (binscatter).

- Intercept shifts down.
- Slope increases (i.e. becomes less negative)
- Rental price gradient actually has the wrong slope. My guess is that this reflects a problem with the Zillow index, what in Westchester county is like a 3 bedroom house in Manhattan? or that averaging across MSAs is creating a statistical problem.
- ... but this broadly confirms the predictions of the monocentric city model for a decrease in t and A.
- The changes in rents seem much larger than those in prices. What does this suggest? Recall how capitalization works.

Highways and Decentralization in the US

Baum-Snow (2007) looks at how the development of the interstate highway system affected how US cities were organized.
The interstate highways system was begun in the mid 1950's and most of the routes were built by 1970. Most of the expansion since 1970 has involved adding lanes to existing routes.
How did this change how US cities were organized?

- Define constant area 'central cities' using the 1950 census.
- Define constant boundary MSA's from 1990 census.
- What is the change is the central city population share?
- How much of this change was caused by the interstate highway system?

US cities decentralized a lot between 1950 and 1990.

TABLE I
AGGREGATE TRENDS IN SUBURBANIZATION, 1950–1990

	1950	1960	1970	1980	1990	Percent change 1950–1990
Panel A: Large MSAs						
MSA population	92.9	115.8	134.0	144.8	159.8	72
Total CC population	44.7	48.5	51.3	49.2	51.0	14
Constant geography CC population	44.7	44.2	42.6	37.9	37.1	−17
N for constant geog. CC population	139	132	139	139	139	
Panel B: Large Inland MSAs						
MSA population	39.2	48.9	57.0	65.0	73.5	88
Total CC population	16.8	19.7	22.1	22.1	23.2	38
Constant geography CC population	16.8	16.5	15.4	13.3	12.5	−26
N for constant geog. CC population	100	94	100	100	100	
Total U. S. population	150.7	178.5	202.1	225.2	247.1	64

Notes: All populations are in millions. CC stands for central city. The sample includes all metropolitan areas (MSAs) of at least 100,000 people with central cities of at least 50,000 people in 1950. The sample in Panel B excludes MSAs with central cities located within 20 miles of a coast, major lake shore, or international border. MSA populations are for geography as of year 2000. Constant geography central city population uses 1950 central city geography. From Baum-Snow (2007).

Next estimate a density gradient,

$$
\begin{aligned}
P_{ij} &\sim \text{Pop Density, tract } j\text{, MSA } i \\
\text{dis}_{ij}^{\text{cbd}} &\sim \text{distance to CBD} \\
\text{dis}_{ij}^{\text{hwy}} &\sim \text{distance to nearest highway}
\end{aligned}
$$

Now estimate,

$$P_{ij} = \alpha_i + \beta \text{dis}_{ij}^{\text{cbd}} + \gamma \text{dis}_{ij}^{\text{hwy}} + \epsilon_{ij}$$

This is a density gradient, but (1) worry about how density changes with two distances, (2) it's in levels not logarithms. (This is a little odd, recall what the land rent gradients for Japan looked like: not linear).

THE SPATIAL DISTRIBUTION OF METROPOLITAN AREA POPULATIONS

Panel A: 1970 and 1990 Cross-Sections

Sample		Log population density 1970	Log population density 1990
Large MSAs in 1950 (36,250 tracts, 139 MSAs)	Distance to CBD	−.132 (.001)**	−.114 (.001)**
	Distance to highway	−.014 (.002)**	−.019 (.002)**
Large MSAs in 1950 with central cities at least 20 miles from a coast or border (17,336 tracts, 100 MSAs)	Distance to CBD	−.134 (.002)**	−.117 (.001)**
	Distance to highway	−.055 (.003)**	−.054 (.003)**

Notes: Each pair of entries lists coefficients and standard errors from a regression of log population density on the listed variables at the census tract level. All regressions include MSA fixed effects. All distances are in miles. From Baum-Snow (2007).Population density is higher near CBDs and highways, but less so over time. Census tract level data show that people in US cities are spreading out, too.

Here is an example for a particular city in Texas.

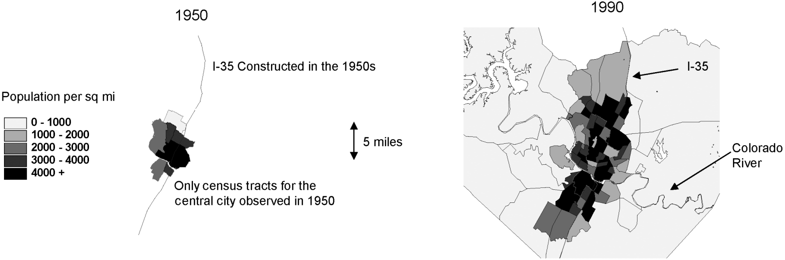


FIGURE II. Development Patterns in Austin, TX.

Estimating equation and reverse causation.

The main regression in the paper is about how the central city share of population changes with the number of highway rays. A ray is a segment of the highway which passes through the central city and out of the MSA. They are radial highways. These are roads that (1) facilitated decentralization (2) are most obviously going to decrease t.

This could all be reverse causation. Hopefully we build highways to places where people want to move anyhow. Much of the paper is about developing an econometric method for addressing this problem. We're not going to talk about this.

Here is the main estimating equation,

$$\Delta \ln N_i^c = \delta_i + \delta_2 \mathrm{ray}_i + \mathrm{controls}_i + \epsilon_i$$

- N_i^c is center city population.
- Δ indicates changes from 1950-90.
- rays are highway rays in 1990. Since there were zero in 1950, this is really changes in rays.
- Controls are important, but I don't want to talk about them.

Recalling rules of logarithms,

$$
\begin{aligned}
\Delta \ln N_i^c &= \ln N_{1990i}^c - \ln N_{1950i}^c \\
&= \ln \frac{N_{1990i}^c}{N_{1950i}^c} \\
&= \ln(1 + r_N) \\
&\sim r_N
\end{aligned}
$$

So, as long as the rate of change is not so big that $ln(1+x) \sim x$ is not a good approximation, this δ_2 tells us the percentage change in central city population caused by each ray, r_N.

Long-Difference Regressions of the Determinants of Constant Geography Central City Population Growth, 1950–1990

Large MSAs in 1950

		Change in log population in constant geography central cities				
	OLS3	IV1	IV2	IV3	IV4	IV5
Change in number of rays	−.059	−.030	−.106	−.123	−.114	−.101
	(.014)**	(.022)	(.032)**	(.029)**	(.026)**	(.046)*
1950 central city radius	.080		.111	.113	.106	.125
	(.014)**		(.023)**	(.023)**	(.023)**	(.021)**
Change in simulated log income	.084			.048	−6.247	−.137
	(.378)			(.417)	(6.174)	(.480)
Change in log of MSA population	.363			.424	.374	.405
	(.082)**			(.094)**	(.079)**	(.108)**
Change in Gini coeff of simulated income					−23.416	
					(23.266)	
Log 1950 MSA population						−.062
						(.062)
Constant	−.640	−.203	−.359	−.588	4.580	−.611
	(.260)*	(.078)*	(.076)**	(.281)*	(5.091)	(.265)*
Observations	139	139	139	139	139	139
R-squared	.39	.00	.01	.30	.33	.37

Notes: In columns IV1-IV5, the number of rays in the 1947 plan instruments for the change in the number of rays. Standard errors are clustered by state of the MSA central city. Standard errors are in parentheses. ** indicates significant at the 1 percent level, * indicates significant at 5 percent level.

Back to the monocentric city model...

- Each interstate ray causes about a 10% reduction in CC population between 1950 and 1990.
- There were about 2.6 new radial highways in an average MSA between 1950 and 1990 (1 highway counts as 2 rays)
- So the interstate accounted for about a 25% decrease in central city population.
- From 1950 to 1990, central city population fell by about 20%.
- ... so the highways alone can account for all decentralization of population between 1950 and 1990.
- If we think that the main way highway worked was to reduce transportation costs, then this looks pretty good for the moncentric city model. The monocentric city model says we need a decreasing share of population near the center as t falls.

Highways and Growth

- A second prediction of the monocentric city model is that cities will grow when transportation cost falls.
- Duranton and Turner (2012) examine this hypothesis by looking at how MSA population (really employment) changes with lane miles of interstate highway between 1983 and 2003.
- Like Baum-Snow (2007) we hope that we build highways in cities where people want to move, so reverse causation is an issue. Much of this paper is about a technique for addressing this problem (similar to Baum-Snow et al. (2017)) but we're not going to talk about it.

TABLE 1
Summary statistics for our main variables

	Mean	Standard deviation
1983 Employment ('000)	250·5	588·4
2003 Employment ('000)	410·7	861·9
1983–2003 Annual employment growth (%)	2·8	1·2
1983 Interstate highways (km)	243·4	297·0
2003 Interstate highways (km)	255·2	309·4
1983 Interstate highways per 10,000 population (km)	6·4	6·8
2003 Interstate highways per 10,000 population (km)	5·1	4·0
Planned 1947 highways (km)	117·6	128·1
1898 Railroads (km)	286·1	298·2
1528–1850 Exploration route index	3031·9	4270·7

Note: Averages are across all 227 MSAs. Duranton and Turner (2012).

Cities grew a lot between 1983 and 2003. The highway network grew a little. Did growth in the highway network cause city growth? How much?

Here is the main estimating equation from Duranton and Turner (2012).

$$\Delta \ln n_{it+1} = A_0 + A_1 \ln r_{it} + A_2 \ln n_{it} + A_3 x_{it} + \varepsilon_{it}$$

Where

$$\begin{aligned} n_{it} &\sim \text{Employment in MSA } i \text{ at year } t \\ r_{it} &\sim \text{Lane miles of interstate in MSA } i \text{ in year } t \\ x_{it} &\sim \text{Control variables we won't talk about} \end{aligned}$$

This looks just like the Baum-Snow regression, but there is an important difference. Since Baum-Snow started his study when there were zero interstates, his control for highway rays was really 'change in rays'. That's not what's happening here. Here employment growth is a function of the initial level of highway lane miles. It's actually quite hard to compare the two regressions, even though they look a lot alike.

As before,

$$\begin{aligned}\Delta \ln n_{it+1} &= \ln n_{it+1} - \ln n_{it} \\ &= \ln(n_{it+1}/n_{it} \\ &= \ln(1+\rho_n) \\ &\approx \rho_n\end{aligned}$$

So that A_1 tells us the effect on the growth rate of the MSA employment from a change in initial lane miles of interstate.

In fact, A_1 is an elasticity. Suppose we increase r_n by 1%, all else equal. Then we have

$$
\begin{aligned}
\Delta \ln n^1_{it+1} - \Delta \ln n^0_{it+1} &= A_0 + A_1 \ln(1.01 r_{it}) + A_2 \ln n_{it} + A_3 x_{it} + \varepsilon_{it} - \\
&\quad A_0 + A_1 \ln(r_{it}) + A_2 \ln n_{it} + A_3 x_{it} + \varepsilon_{it} \\
&= A_1 \ln(1.01 r_{it}) - A_1 \ln(r_{it}) \\
&= A_1 \ln(1.01) + A_1 \ln(r_{it}) - A_1 \ln(r_{it}) \\
&= A_1 \ln(1.01) \\
&= A_1 \times 0.01
\end{aligned}
$$

This means that a 1% increase in r_{it} causes an increase in ρ of about $A_1 \times 0.01$.

TABLE 3

Growth of employment and roads as a function of initial roads, IV

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Panel A: Employment or population growth								
ln(Int. Hwy km$_{83}$)	0·13**	0·15***	0·15***	0·16***	0·13**	0·096*		0·13***
	(0·056)	(0·037)	(0·043)	(0·047)	(0·054)	(0·053)		(0·030)
ln(Emp$_{83}$)	−0·11***	−0·26	−0·27	−0·27	−0·27	−0·28	−0·30	0·24***
	(0·037)	(0·19)	(0·19)	(0·19)	(0·21)	(0·21)	(0·19)	(0·075)
ln(USGS maj. roads$_{80}$)							0·29***	
							(0·084)	
Over-id p value	0·04	0·96	0·93	0·59	0·65	0·59	0·18	0·47
Panel B: Road growth								
ln(Int. Hwy km$_{83}$)	−0·27***	−0·28***	−0·26***	−0·26***	−0·28***	−0·25**		
	(0·086)	(0·093)	(0·099)	(0·097)	(0·10)	(0·10)		
ln(Emp$_{83}$)	0·21***	0·25**	0·26**	0·26**	0·14	0·017	0·34**	
	(0·050)	(0·11)	(0·11)	(0·12)	(0·091)	(0·099)	(0·17)	
ln(USGS maj. roads$_{80}$)							−0·53**	
							(0·23)	
Over-id p value	0·42	0·41	0·54	0·57	0·72	0·96	0·47	
$\{\ln(\mathrm{Pop}_t)\}_{t\in\{20,\ldots,70\}}$	N	Y	Y	Y	Y	Y	Y	Y
Physical geography	N	N	Y	Ext.	Ext.	Ext.	N	N
Socioeconomic controls	N	N	N	N	Y	Y	N	N
Census divisions	N	N	N	N	N	Y	N	N
First-stage statistic	17·0	13·3	11·8	13·9	11·3	9·7	11·9	13·3

Notes: 227 observations for each regression. All regressions include a constant. Robust standard errors in parentheses. *,**,***: significant at 10%, 5%, 1%. Panel A: dependent variable is ln Emp in columns 1-7 and ln Pop in column 8. Panel B: dependent variable is ln Interstate Highway kilometres. All regressions use 1947 planned highway kilometres, 1898 kilometres of railroads, and index of 1528-1850 exploration routes as instruments. Duranton and Turner (2012).

Recalling the last slide, we have $A_1 \approx 0.1$, so a 1% increase in lane miles increases the employment growth rate by about $0.1 \times 1\%$, a tenth of a percent.

To get a sense for this magnitude, the average growth rate in employment for these 227 MSAs was about 2.8% per year.
On average, lane miles grew from 243 to 255 km per MSA from 1983 to 2003. This is growth rate of $\frac{255}{243} - 1 \approx .05$ over 20 years.
To find the annual rate of highway growth, we want to solve

$$\nu^{20} = 1.05$$
$$\implies \nu = 1.05^{\frac{1}{20}} \approx 1.0025$$

or, about 0.25% per year.

This means, on average, that highway construction contributes $0.25\% \times 0.1 = 0.025\%$ per year to the baseline 2.8% growth rate of MSA employment. This is the right sign, but the magnitude is very small.

Subways, decentralization and growth

We're interested in evaluating whether the predictions of the monocentric city model are right.

If changes to transportation costs affect the way cities are organized, it shouldn't matter if changes result from better roads, more telecommuting, or better subways. We've checked telecommuting and roads, Gonzalez-Navarro and Turner (2018) check subways.

This paper is based on the following data

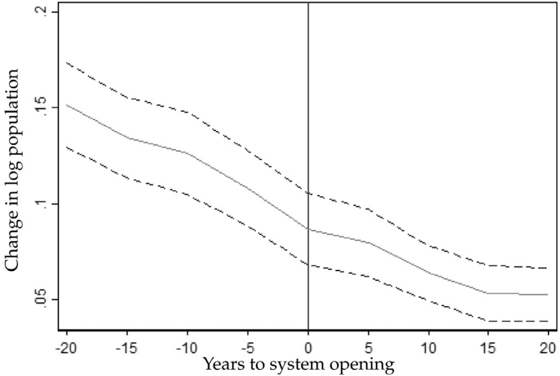
- Census of subways
- Lights at night
- UN City population

Table 1
Descriptive statistics for the world's cities and cities with subway systems in 2010.

	World	Africa	Asia	Europe	N. America	S. America
All cities						
N	632	71	347	57	99	56
Mean population	2427	2091	2509	1921	2441	2825
Mean log(Pop.)	14.3	14.3	14.3	14.2	14.3	14.4
Mean Δ_t log(Pop.)	0.18	0.24	0.20	0.05	0.14	0.19
Mean Δ_t^2 log(Pop.)	-0.010	-0.013	-0.008	-0.005	-0.013	-0.015
Mean light gradient	-0.79	-0.85	-0.78	-0.72	-0.69	-0.96
Mean light intercept	11.0	10.5	10.8	10.8	10.8	12.7
Cities with subway in 2010						
N	138	1	53	40	30	14
Total stations	7886	51	2977	2782	1598	478
Total route km	10,672	56	4210	3558	2219	627
Mean stations	57	51	56	70	53	34
Mean route km	77	56	79	89	74	45
Mean subway lines	4.5	2.0	4.1	5.8	4.7	2.6
Δ_t Stations	3.5	3.9	4.2	3.8	2.5	2.2
Mean log(Stations)	3.60	3.95	3.55	3.90	3.38	3.30
Mean Δ_t log(Stations)	0.23	0.30	0.26	0.22	0.21	0.23
Mean population	4706	11,031	5950	2259	4813	6300
Mean log(Pop.)	14.93	16.22	15.15	14.37	15.05	15.34
Mean Δ_t log(Pop.)	0.11	0.12	0.14	0.04	0.12	0.17
Mean Δ_t^2 log(Pop.)	-0.011	-0.014	-0.012	-0.005	-0.013	-0.017
Mean light in 25km disk	122	212	117	95	170	109
Corr. lights & pop.	0.67		0.67	0.69	0.78	0.91
Mean light gradient	-0.72	-0.62	-0.78	-0.71	-0.58	-0.80
Mean light intercept	11.2	11.0	11.8	11.0	10.2	11.9

Note : Population levels reported in thousands. All entries describing levels report 2010 values. Entries describing changes are averages over the period from 1950 to 2010. Gonzalez-Navarro and Turner (2018).

- There were 138 subway systems in operation in 2010.
- Population data is available for most of these cities, at about 5 year intervals, from 1950-2010.
- 61 cities opened a subway between 1970 and 1990, so there is 20 years of pre- and post population data.
- Do cities grow faster when they get subway stations?
- To check, calculate the mean of $\ln Pop_t - \ln Pop_{t-5}$ over all cities with subways in t and $t-5$, (i.e., the population growth rate) against the years since the city's subway system opened.



Notes: Subway system opening and population growth (constant sample of 61 cities). The graph depicts mean change in city log population according to time to system opening. $t = 0$ indicates the year in which a city's subway system was inaugurated. We impose a constant sample of cities on either side of $t = 0$. Graph based on constant sample of 61 cities. It does not look like subways cause population growth. Gonzalez-Navarro and Turner (2018).

Growth rates in subway cities are falling over time. There is no break in the level or trend of population growth around the time of subway opening. If subways cause population growth, the effect is small.

Density gradients, again I

Gonzalez-Navarro and Turner (2018) want to use the lights at night data to measure how cities decentralize in response to subways.
To do this, they are going to estimate a ‘lights gradient’ for each city year, and ask how this gradient changes with subways.
This process has two distinct steps. First, estimate light gradients for each city year.

- For each of about 137 subway cities, for each year when they observe night lights (1995,2000,2005,2010), calculate mean light intensity in a series of donuts, 0-1.5km, 1.5-5km, 5-10km, 10-25km and 25-50km.
- Let y_i be light intensity in a donut for city i.
- Let x_i be distance of the midpoint of the donut from center, e.g., 7.5 km for 5-10km donut.

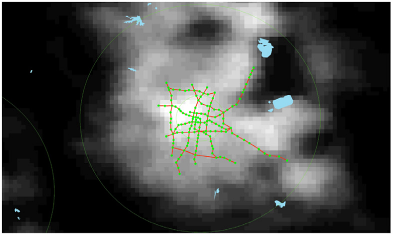
Density gradients, again II

- Estimate city year specific light density gradients,

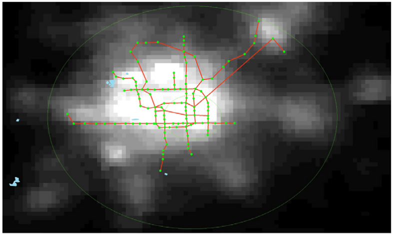
$$\ln y = A + B \ln x + \epsilon$$

This gives a separate B for each city year (estimated from 5 observations). Note that these exactly the same log-linear gradients we've seen before for land rent, just with a different left hand side variable.

Here is what the lights at night data looks like.



Mexico City: 20.1m pop and 147 stations



Beijing: 15m pop and 124 stations

Fig 2: Images show 2010 radiance calibrated lights at night, 2010 subway route maps, and all subway stations constructed prior to 2010. The gray/green ellipses in each figure are projected 5 km and 25 km radius circles to show scale and light blue is water. Gonzalez-Navarro and Turner (2018).

Once they estimate decay parameters B_{it} for city years *it*, they want to check if subways cause cities to spread out. Since lights gradient are downward sloping, if subways cause cities to decentralize, they will INCREASE B.

To check this, they estimate the following regression,

$$\Delta B_{it} = A_0 + A_1 \Delta \ln(\text{subway stations}_{it}) + A_3 \text{controls}_{it} + \epsilon_{it}$$

Here is what they find...

Table 10
Decentralization - Radiance calibrated light gradient.

Panel a - Light gradient					
Dependent variable:	Light gradient	ΔLight Gradient			
Estimation:	OLS	OLS	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)
$\Delta\ln$ (subway stations$_t$)		0.023***	0.024***	0.047*	0.060**
		(0.0062)	(0.0062)	(0.025)	(0.024)
ln (subway stations$_t$)	0.034***				
	(0.010)				
Δ ln(GDPpc_t)		-0.078	-0.079	-0.100*	-0.11*
		(0.053)	(0.053)	(0.056)	(0.058)
Δ ln(COUNTRY POP$_t$)		-0.0051	-0.0014	-0.091	-0.13
		(0.17)	(0.17)	(0.21)	(0.22)
ln(GDPpc_t)	0.043*				
	(0.024)				
ln(COUNTRY POP$_t$)	0.048***				
	(0.014)				
ln(pop$_{t-2}$) control			Yes		Yes
Mean of dep. variable	-0.811	0.041	0.041	0.041	0.041
Mean of subways regressor	3.06	0.36	0.36	0.36	0.36
SD subways regressor	1.49	0.82	0.82	0.82	0.82
R-squared	0.35	0.19	0.19	0.17	0.15

For each city-year, a linear regression was estimated between the log mean radiance calibrated light intensity in successive rings at 0-1.5km, 1.5-5km, 5-10km, 10-25km and 25- 50km and log distance from the city center centroid. Panel A column 1 dependent variable is the slope of the light gradient. Columns 2-5 use as dependent variable the change in slope over a 5 year period. Stars denote significance levels: * 0.10, ** 0.05, *** 0.01. Gonzalez-Navarro and Turner (2018).

Another prediction of the monocentric city model is that cities will be bigger as their amenities are better. Here is some strong evidence for this.

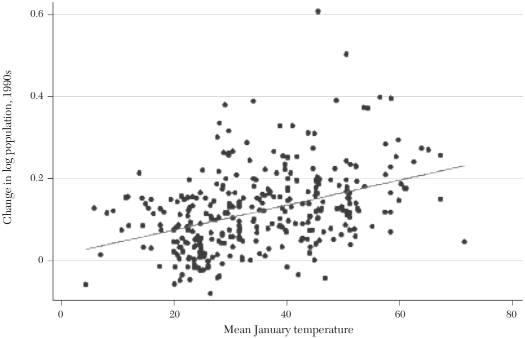


Figure 4. Population Growth and Temperature

Notes: Units of observation are Metropolitan Statistical Areas under the 1999 definitions, using Primary Metropolitan Statistical Areas rather than Consolidated Metropolitan Statistical Areas where applicable and New England County Metropolitan Areas where applicable. Population data are from the Census, as described in the Data Appendix. Mean January temperature is from the City and County Data Book, 1994.

The regression line is *Population growth* $= 0.0030$ [0.0004] $\times$ *Temperature* $+ 0.02$ [0.01]. $R^2 = 0.16$ and $N = 316$.

Glaeser et al. (2001) look at how city growth rates respond to various city level amenities.

To do this, they perform regressions of the form

$$\Delta \ln Pop_{it} = A_0 + A_1 \text{Some Amenity}_{it} + \text{controls}_{it} + \epsilon_{it}$$

	Population Growth	
UNITED STATES (77-95)	**Estimate**	**t-value**
Temperate climate	0.35	17.8
Proximity to ocean coast	0.24	12.5
Live performance venues per capita	0.14	6
Dry climate	0.12	6.5
Restaurants per capita	0.05	2.9
Art galeries and museums per capita	-0.03	-1.5
Movie theaters per capita	-0.05	-2.6
Bowling alleys per capita	-0.19	-11.3
FRANCE (1975-1990)		
Restaurants per capita	0.45	5
Hotel rooms per capita	0.33	4
ENGLAND (1981-1997)		
Tourist nights per capita	0.31	2.7

Notes: Each coefficient is based on a separate regression. The temperate climate variable is the inverse of average temperature per year minus 70 degrees. All temperatures are measured in Fahrenheit degrees. Dry climate stands for the inverse of average precipitation. US regressions included controls for county density, share of college educated, and a shift-share industry growth measure. France observation units are the "Zones d'Emploi". France regressions included controls for participation rate and population in l975. The England regression is for counties, as defined in the Data Appendix. The England regression included a dummy for Northern counties and initial population as controls. **?**.

This suggests a pretty strong relationship between amenities and population growth, but reverse causation is clearly a concern for some of these variables.

Property taxes I

One of the more interesting consequences of spatial equilibrium is that property taxes are capitalized into land prices in a really mechanical way. One dollar of property taxes equals one dollar of rent, and one dollar of property taxes per year equals the discount present value of one dollar per year in asset prices.

In reality, things ought to be more complicated for two reasons.

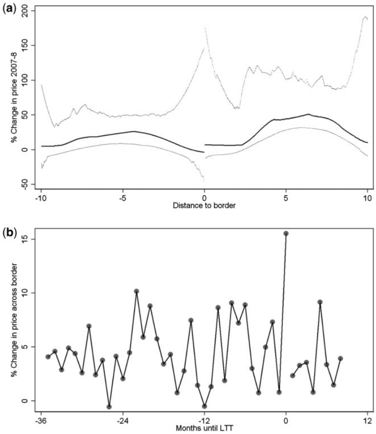
Property taxes II

- Property taxes are assessed on the value of house and land. If you put an addition on your house, you need to pay property taxes on the value of the addition forever. Similarly for a new paint job, etc. Thus, if we allow a little more realistic description of the world, we might expect that 1$ of property taxes will decrease the value of the HOUSE by more than 1$ because it will lead to sub-optimal maintenance. More on this later.

Property taxes III

- Up to now, we have implicitly assumed that property taxes leave the model. They go to the city government and they are entirely wasted. In fact, property taxes are used, at least in part, to provide important public services like trash collection, fire and police protection, parks and roads. These things will operate like amenities, and hopefully, have value of at least 1$ per dollar of taxes collected. Strictly, property taxes decrease the value of a property ALL ELSE EQUAL, but this is a hard situation to observe.

- In 2008, Toronto imposed a ‘land transfer tax’.
- This was a property tax that you had to pay whenever you sold your property, rather than every year, the way property taxes are usually collected.
- This tax was imposed in Toronto, but not in neighboring municipalities.
- Think about what should happen to property prices when we cross the municipal border from Toronto into a surrounding municipality?
- We should see prices fall in Toronto by about the magnitude of the tax, net of whatever value of public services the tax will purchase.
- Dachis et al. (2012) do exactly this experiment, and this is just about what they find (though their estimates are very imprecise).



Price of residential real estate transactions across the Toronto border. (a) Vertical axis is percentage change in the price after the imposition of the LTT. Horizontal axis is distance from the Toronto municipal border, negative distances are suburban, positive distances are Toronto. Solid line gives mean percentage change in price and dotted lines are 95% and 5% confidence bounds. (b) Vertical axis is percentage change in price from crossing the Toronto border before and after the imposition of the LTT. Horizontal axis counts months from the imposition of the LTT.

- Palmon and Smith (1998) finds another way to look for changes in property tax rates, all else equal.
- Data describes house prices in 50 subdivisions in the Houston suburbs.
- Three school districts serve all 50, and have similar quality and tax rates.
- Water and sewer service was provided by private developers to each subdivision.
- Water and sewer service is the same in all subdivisions.
- Construction was paid for with a bond issue, financed by property taxes.
- The interest rate on the bonds, and hence the subdivision property tax rate, varies with the interest rate that prevailed when construction occurred.

- That is, the different subdivisions are paying different prices for the same services.
- Their sample is only 500 transactions, and their estimation is pretty complicated, but they find that about 65 cents of every dollar of property tax is capitalized into property prices.

Another prediction (and the last one we'll check) of the monocentric city model is that a 1$ increase in wages will lead to a 1$ increase in land rent everywhere.

We can find some evidence about this in Davis and Ortalo-Magné (2011).

This paper looks at the relationship between income and expenditure on housing using a large census data set. They find pretty strong evidence that people spend about 25% of their income on housing, no matter what.

Here is their main table,

Table 1
Median ratio of rental expenditures to wage and salary income, median income, and growth in real rental prices.

MSA	Median ratio			Median HH income (2000) renters only	Real rent growth, 1980–2000
	1980	1990	2000		
Albany–Schenectady–Troy	0.21	0.23	0.23	$32,300	16.2%
Atlanta–Sandy Springs–Marietta	0.24	0.25	0.25	$36,300	25.1%
Austin–Round Rock	0.27	0.25	0.25	$36,400	42.0%
Bakersfield	0.28	0.25	0.25	$26,800	0.7%
Baltimore–Towson	0.23	0.23	0.23	$34,000	35.1%
Boston–Cambridge–Quincy	0.24	0.26	0.24	$43,000	52.1%
Buffalo–Niagara Falls	0.20	0.22	0.23	$28,800	21.1%
Charlotte–Gastonia–Concord	0.23	0.24	0.24	$37,000	27.3%
Chicago–Naperville–Joliet	0.21	0.23	0.23	$36,000	33.5%
Cincinnati–Middletown	0.21	0.22	0.20	$30,400	5.5%
Cleveland–Elyria–Mentor	0.21	0.22	0.23	$30,000	5.1%
Columbus	0.22	0.23	0.23	$33,100	38.6%
Dallas–Fort Worth–Arlington	0.24	0.24	0.24	$34,600	32.5%
Denver–Aurora	0.25	0.24	0.26	$35,000	19.5%
Detroit–Warren–Livonia	0.21	0.22	0.22	$35,000	6.8%
Fresno	0.25	0.27	0.26	$25,900	14.0%
Grand Rapids–Wyoming	0.19	0.24	0.21	$31,000	16.9%
Greensboro–High Point	0.24	0.23	0.22	$33,000	23.7%
Houston–Sugar Land–Baytown	0.23	0.22	0.23	$32,000	7.2%
Indianapolis–Carmel	0.21	0.23	0.23	$34,000	8.6%
Jacksonville	0.27	0.24	0.25	$31,000	3.5%
Kansas City	0.21	0.22	0.22	$35,700	21.4%
Las Vegas–Paradise	0.29	0.27	0.27	$35,000	20.1%
Los Angeles–Long Beach–Santa Ana	0.25	0.29	0.27	$33,000	37.2%
Louisville–Jefferson County	0.22	0.23	0.21	$32,000	4.2%
Miami–Fort Lauderdale–Pompano Beach	0.27	0.29	0.29	$28,000	24.3%
Milwaukee–Waukesha–West Allis	0.20	0.23	0.22	$32,000	12.2%
Minneapolis–St. Paul–Bloomington	0.24	0.25	0.23	$35,500	19.3%
Nashville–Davidson–Murfreesboro–Franklin	0.23	0.24	0.24	$33,000	22.9%
New Orleans–Metairie–Kenner	0.24	0.25	0.24	$25,000	24.6%
New York–Northern New Jersey–Long Island	0.22	0.24	0.24	$39,600	38.2%
Orlando–Kissimmee	0.26	0.27	0.27	$32,950	41.1%
Philadelphia–Camden–Wilmington	0.22	0.24	0.23	$37,000	33.2%
Phoenix–Mesa–Scottsdale	0.28	0.26	0.26	$32,000	9.5%
Pittsburgh	0.21	0.21	0.22	$30,000	10.1%
Portland–Vancouver–Beaverton	0.27	0.24	0.25	$36,000	19.1%
Riverside–San Bernardino–Ontario	0.26	0.28	0.27	$32,000	17.9%
Sacramento–Arden-Arcade–Roseville	0.25	0.28	0.26	$33,000	38.9%
St. Louis	0.22	0.23	0.22	$30,000	4.4%
Salt Lake City	0.24	0.23	0.27	$30,900	22.5%
San Antonio	0.22	0.24	0.24	$30,000	13.5%
San Diego–Carlsbad–San Marcos	0.29	0.30	0.28	$34,000	38.4%
San Francisco–Oakland–Fremont	0.26	0.28	0.25	$46,900	70.7%
San Jose–Sunnyvale–Santa Clara	0.24	0.26	0.25	$58,500	110.0%
Seattle–Tacoma–Bellevue	0.25	0.25	0.26	$38,200	33.7%
Syracuse	0.24	0.24	0.24	$27,000	16.7%
Tampa–St. Petersburg–Clearwater	0.26	0.25	0.25	$31,400	23.0%
Tucson	0.26	0.29	0.26	$24,600	−2.7%
Tulsa	0.23	0.22	0.23	$31,000	1.8%
Washington–Arlington–Alexandria	0.23	0.26	0.24	$44,600	46.7%
Average	0.24	0.25	0.24	$33,689	24.2%
Standard deviation	0.02	0.02	0.02	$5710	19.4%

This figure from Glaeser and Gottlieb (2009) makes this point nicely, too

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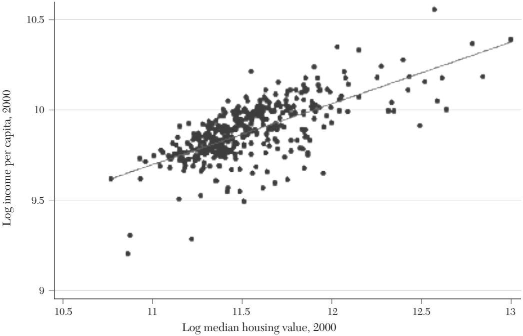

Figure 3. Housing Prices and Income

Notes: Units of observation are Metropolitan Statistical Areas under the 2006 definitions. Data are from the Census, as described in the Data Appendix.

The regression line is $\log income = 0.34\ [0.02] \times \log value + 5.97\ [0.22]$.
$R^2 = 0.46$ and $N = 363$.

- This is really interesting, but I think it is only suggestive.
- Clearly wages and housing expenditure move together, as the monocentric city model suggests.
- ... but the effect is much less than one-for-one as the model requires. The model is clearly too simple to describe these data. We need to be able to distinguish between housing and land (next topic).
- Maybe housing is a normal good and rich people by more of it?
- Davis and Ortalo-Magné (2011) are looking at expenditure on housing, not the amount of housing actually consumed. The model says that the IDENTICAL bit of housing, $\bar{\ell}$, has a different price as wages change. This is not quite what we're seeing here.

...and one final thing.

Many cities have minimum wages (`https://www.epi.org/minimum-wage-tracker/`).

If the moncentric city model is right, what should happen?
How should the result in Davis and Ortalo-Magné (2011) lead us to adjust this prediction?

Three Brown Ph.D students (Borg, Gentile, Hermo) have looked and find some evidence that minimum wages are capitalized into the rental prices for inexpensive apartments, but it is not clear how big the effect is.

The state of the evidence I

- $R(x)$ decreasing in x. This is broadly consistent with observation. Gupta et al. (2021) gives us another instance.
- Commuting costs,
  - As people reduced the frequency of their commute due to COVID/remote work, rent and asset prices gradients flattened, EXACTLY as predicted.
  - As commuting costs fall due to highways or subways, population/lights spread out EXACTLY as predicted.
  - As commuting costs fall due to highways or subways, weak or no effect on population growth. This is not what we expected. Strictly, the model makes predictions about levels, not changes, but this is still a puzzle.
- As wages, w, increase,

The state of the evidence II

  - Expenditure on housing increases by about 1$ for each 4$ of income. This is the right sign, but the magnitude is small. Maybe we need 'housing' in the model instead of land? Maybe we need to measure the quantity of housing rather than expenditure on housing.
  - There is some preliminary evidence that minimum wages are partly capitalized into the price of inexpensive rental units.
- As amenities, A increase,
  - Pretty consistent evidence for an increase in the growth of city population. This is not exactly what the model predicts, but it is close. The model predicts the level of population will increase with amenities.
  - Central city rent goes down with COVID, so markets capitalize the 'COVID disamenity' as the model suggests it should.

The state of the evidence III

- Property taxes are capitalized into asset price much in the way the model suggests. The model is clearly not quite rich enough to treat this properly, but empirically, a good guess would 60-100% capitalization of property taxes.

This is pretty good for so simple a model.

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