Sewers and Urban Development

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December 3, 2024

How does sewer construction affect the development of cities? I

- We are more productive if we work at higher densities, and with different people than we want to live with. Cities are how we solve this problem. Understanding what affects our tolerance of density is central to understanding how cities are organized.
- Rank the most important things a local government does for you, e.g.; water, law and order, sewer, fire, other public health, transportation, schools. Sewers are understudied.
- The absence of sewers is one of the defining features of slums. How does the provision of modern sanitation change slums? What is the incidence of this change?
- Are the effects of sewers on cities the same everywhere? (as seems to be the case for roads).

Literature

- Water and sewer infrastructure has large, well documented effects on health in the developing world [Ashraf et al., 2017, Bhalotra et al., 2021, Galiani et al., 2005] and in developed world cities in the late 19th/early 20th centuries [Alsan and Goldin, 2019, Anderson et al., 2018, Ferrie and Troesken, 2008]).
- Sewers have no effect on infant mortality in Brazil 1990-2010 [Gamper-Rabindran et al., 2010].
- Sewers have a large effect on land prices in late 19th century Chicago [Coury et al., 2022].
- There does not seem to be a lot of sorting in response to sewers [Alsan and Goldin, 2019].

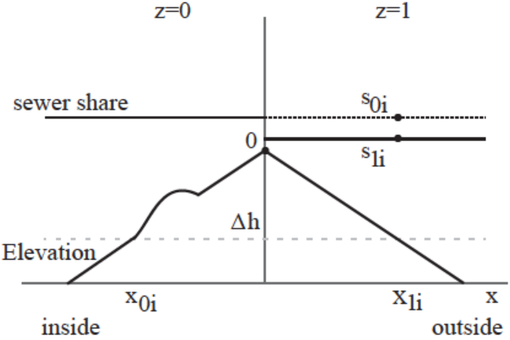
$\Longrightarrow$ weak prior that sewers lead to large increase in density and not much change in demographics. No prior over heterogeneity of effects.

Identification I

- Sewers work on gravity. Moving sewage on a grade of less than 1:200 is hard. Uphill is harder.
- Sewer networks generally serve a (part of a) single drainage basin.
- Two census tracts on opposite sides of a basin divide should be similar (on average), but one may require moving sewage uphill to get to an existing sewer network.

How can we use this intuition to think about the effect of sewer service on urban development?

Identification with a discontinuity in sewer share

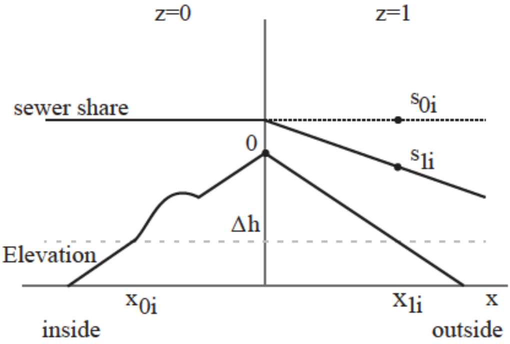


Plot of elevation and sewer share in a neighborhood of a basin divide. 'inside' is uphill from existing network. x is distance to the basin divide. Elevation is relative to basin divide.

Treatment is $s_0 - s_1$. Without independent effects of elevation or x, inside is a control for outside.

$\Longrightarrow z = \mathbb{1}(x \text{ is outside})$

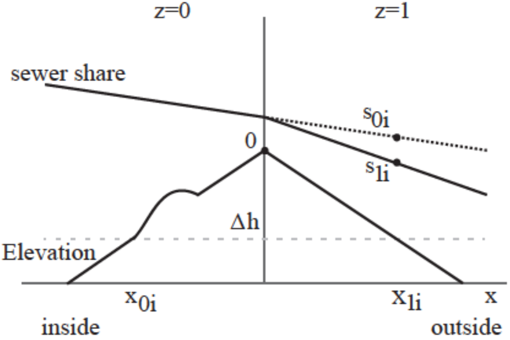
Identification with a kink in sewer share



No strong prior over whether crossing a basin divide will lead to a step or a kink in sewer share. It depends on the scale over which costs increase.

$\Longrightarrow z = \mathbb{1}(x \text{ is outside}) \times x$

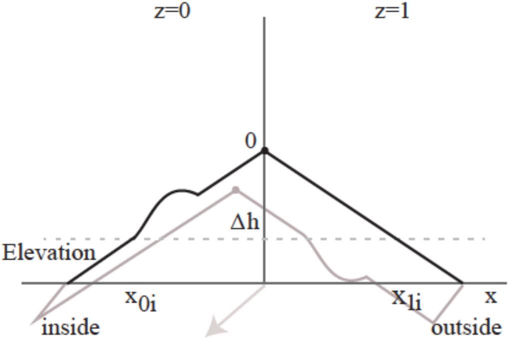
Identification with a kink in sewer share and trend in x



Distance to the basin divide may have an independent effect on sewer share. We need to look for a kink (or step) in sewer share net of the effect of x displacement.

$\Longrightarrow$ control for x

Identification, elevation vs displacement



Distance to the basin divide and climbing to the elevation divide should both matter. With elevation, we can exploit variation independent of x.

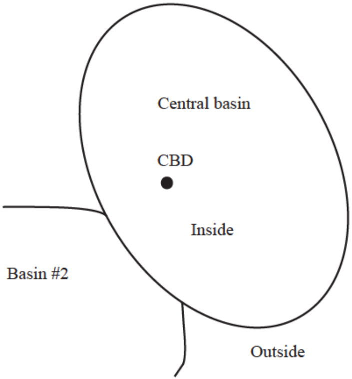
$\Longrightarrow z = \mathbb{1}(x \text{ is outside}) \times \Delta h$

Identification, further issues

- Taking gravity as given, crossing a basin divide must increase the cost of sewer access for otherwise similar locations.
- Magnitude of cost shock increases with horizontal and vertical displacement to basin divide for locations outside the basin.
- To turn this intuition into a research design, we need an empirical analog to the figures.
    - Draw basin divides with DEMs and GIS tools.
    - Define x as 'perpendicular displacement from basin divide'.
    - Define 'inside' as 'in a basin containing a large city'.
    - Translate to a plane? How wide/long a strip should we use?

Geography: Central basins and 'Inside'

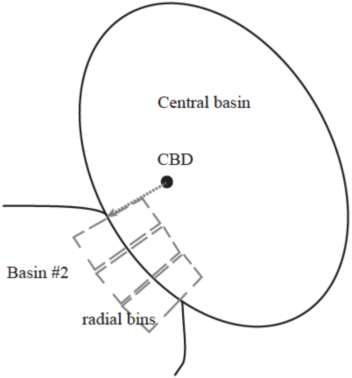
Consider drainage basins containing CBDs. These are 'central basins'. A census tract is 'inside' if its centroid lies in the central basin.



If Basin #2 is also a CBD basin, then 'inside' is defined based on closest CBD.

Geography: Radial bins

Define 'radial bins', 2km wide, and 2×2km deep.



Tract elevation is relative to highest tract centroid in the same radial bin $\leq$ 2km from the basin divide. NB: larger elevations are lower.

Data

Cities

- The UN Cities data is a census of all cities that had a population 300,000 or more in 2014. These data report the location of the center of each city.
- We consider areas (1) near the boundary of the drainage basin containing the city center, and (2) within 75km of the city center.
- We use all Cities in the UN Cities data in; Brazil, Colombia, South Africa, Jordan, and Tanzania.

Data

Sewers

Sewer data all comes from census questions;

- Brazil: ‘Is the bathroom or toilet drain connected to the public sewer system?’
- Colombia: ‘Does your house have sewage service?’
- South Africa: ‘Is the main type of toilet facility used by this household a flush toilet connected to sewerage system’
- Tanzania: ‘Does your house have a flush toilet connected to a piped sewer system?’
- Jordan: ‘Does your house have sanitation connected to a public network?’

We calculate the share of households in a ‘tract’ with sewer access and map the extent of tracts with sewers.

Data

Population density, other outcomes

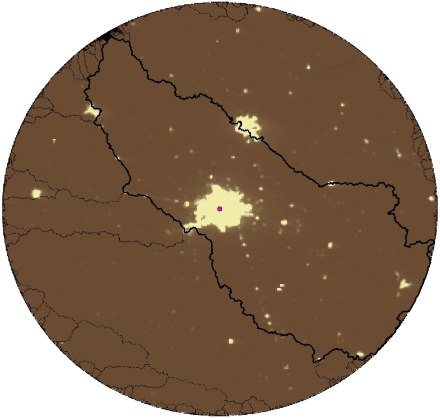
Population density, income measures, and other outcomes all come from the same censuses.

For all countries but Jordan, population density is the full count of people divided by tract area. For Jordan, it is the full count of households divided by tract area.

Data

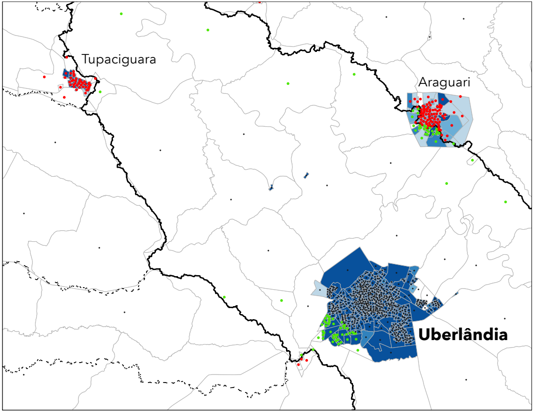
Drainage basins

- Construct drainage basins from digital elevation maps using tools for this purpose in ARCGIS.
- Use two DEMs; the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) DEM and the Shuttle Radar Topography Mission (SRTM) DEM.
- ASTER is derived from stereoscopic imagery that is thought to be less prone than SRTM to confuse trees and rooftops with the ground. We rely primarily on the ASTER DEM, but consider SRTM for robustness checks.
- A comparison with LIDAR data shows that average error of ASTER is about 4m in four small study areas. SRTM is about the same. [Uuemaa et al., 2020].



Drainage basin boundaries in a 75km disk centered on Uberlandia, Brazil. Background is lights at night, grey is all drainage basin boundaries calculated from the ASTER DEM. Black is the boundary of the drainage basin containing the center city.

Sewers and 'Inside' near Uberlandia, Brazil



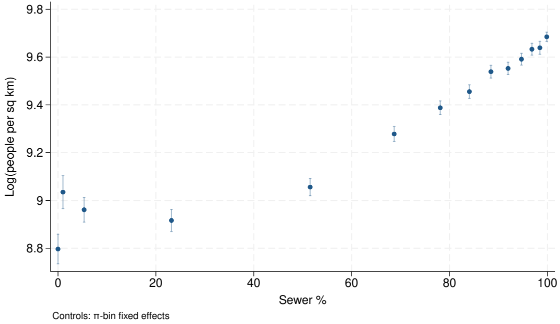
- Blue is sewer share.
- Tracts in the central basin are 'inside'.
- Drop tracts with centroids more than 2km from the basin divide.

Estimation sample; Brazil, Colombia, South Africa, Jordan

	cities	π-bins	tracts	Share inside	Tract area km^2	People/km^2	Sewer share
Brazil	59	1,246	27,373	0.53	0.28	17,523	0.71
Colombia	18	355	23,199	0.53	0.10	28,880	0.72
Jordan	2	8	26	0.35	2.35	878	0.43
South Africa	12	273	3,177	0.52	0.47	8,358	0.77
Tanzania	7	105	1,593	0.65	0.13	24,936	0.08

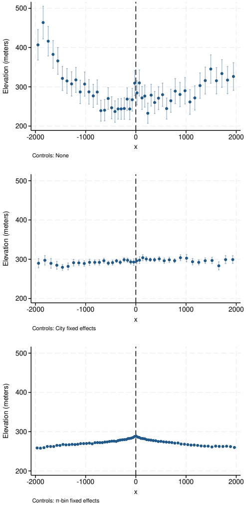
- Jordan is households, not people.
- The economic geography of these places is really different.
- Estimations will be at tract/bin level, so most of the weight will come from Colombia and Brazil.
- Sewers are rare in Tanzania.

Log Population density vs sewer %



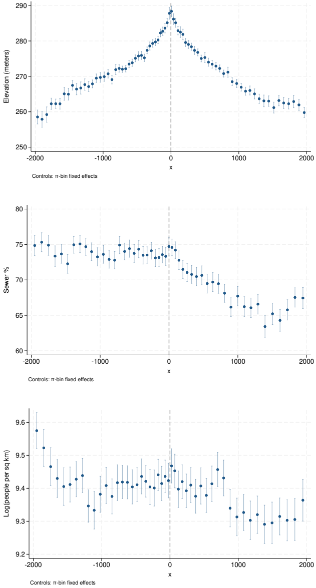
Mean log population density by tract sewer percentage. All tracts within 2km of a basin divide, conditional on radial bin. 100% increase in sewer share increases population density by $\approx e^{0.7} \approx 2.0$.

Why radial-bin controls?

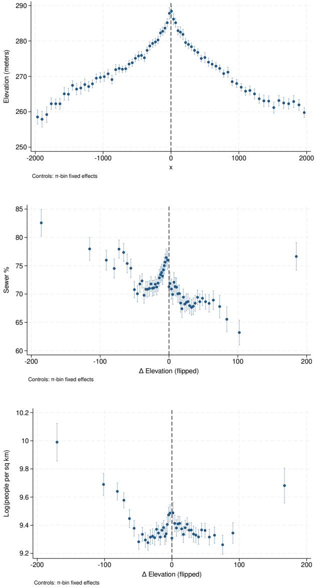


Mean elevation by distance to basin divide; raw data (top), net of segment mean (middle), and net of radial bin mean (bottom). NB: On average the divide is not a dramatic feature.

Identification, $z = \mathbb{1}(x \text{ is outside})$



Identification, $z = \mathbb{1}(x \text{ is outside}) \times \Delta h$



Estimation/Identification (1)

First stage is sewer share by tract as a linear function of

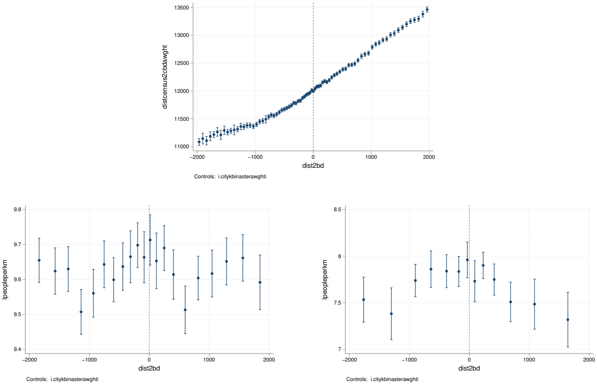
- Controls: Radial bin indicators and radial bin by perpendicular distance. That is, slope and intercept by radial bin. Also Elevation.
- Instruments are: (1) 'outside indicator', (2)'outside indicator times displacement', (3) 'outside indicator times elevation'.

Sewers and population density, Universe

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. OLS									
sewer %	0.0086***	0.0086***	0.0086***	0.0081***	0.0081***	0.0081***	0.0074***	0.0074***	0.0074***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
N	53775	53775	53775	53775	53775	53775	53775	53775	53775
2. First stage									
outside	-0.7760**	-0.5459	-0.5353	-1.3965***	-0.4593	-0.5558	-1.0027***	-0.3917	-0.5815
	(0.3409)	(0.3840)	(0.3841)	(0.3472)	(0.4263)	(0.4265)	(0.3574)	(0.4570)	(0.4577)
x*Outside	-0.0050***		-0.0050***	-0.0055***		-0.0054***	-0.0064***		-0.0064***
	(0.0004)		(0.0004)	(0.0005)		(0.0005)	(0.0006)		(0.0006)
ΔElev*Outside		-0.0144**	-0.0098		-0.0369***	-0.0330***		-0.0184*	-0.0161
		(0.0072)	(0.0073)		(0.0093)	(0.0093)		(0.0102)	(0.0103)
N	53775	53775	53775	53775	53775	53775	53775	53775	53775
3. RF log(pop density)									
outside	0.0335**	0.0778***	0.0780***	0.0307*	0.0891***	0.0846***	0.0064	0.0367*	0.0245
	(0.0147)	(0.0182)	(0.0182)	(0.0159)	(0.0214)	(0.0213)	(0.0161)	(0.0223)	(0.0220)
x*Outside	-0.0001***		-0.0001***	-0.0003***		-0.0003***	-0.0004***		-0.0004***
	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)
ΔElev*Outside		-0.0019***	-0.0018***		-0.0023***	-0.0021***		-0.0008	-0.0007
		(0.0004)	(0.0004)		(0.0005)	(0.0005)		(0.0006)	(0.0006)
N	53775	53775	53775	53775	53775	53775	53775	53775	53775
4. IV log(pop density)									
sewer %	0.0211***	0.0353**	0.0231***	0.0404***	0.0228**	0.0423***	0.0609***	0.0064	0.0606***
	(0.0036)	(0.0154)	(0.0037)	(0.0045)	(0.0089)	(0.0044)	(0.0060)	(0.0158)	(0.0059)
N	53775	53775	53775	53775	53775	53775	53775	53775	53775
F	88.88	5.861	60.00	84.27	17.70	61.20	73.54	5.001	49.99
Elevation	Y	Y	Y	Y	Y	Y	Y	Y	Y
π-bins	Y	Y	Y	Y	Y	Y	Y	Y	Y
x	Y	Y	Y						
seg×x				Y	Y	Y			
π-bins×x							Y	Y	Y

Note: Robust standard errors in parentheses. Significance stars * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure: Placebo and balance tests



Note: *x-axis* $\sim$ *displacement from basin divide. Top: Bin Distance to cbd net of radial bin mean. Bottom: population density for bins where tract mean sewer percentage is above/below (left/right) 90% within 2km of the basin divide.*

Sewers and income, Brazil and South Africa

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. OLS									
sewer %	0.0045***	0.0045***	0.0045***	0.0040***	0.0040***	0.0040***	0.0039***	0.0039***	0.0039***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
N	30549	30549	30549	30549	30549	30549	30549	30549	30549
2. First stage									
outside	-0.9758**	-1.9388***	-1.9299***	-1.5454***	-1.5515***	-1.6363***	-1.4198***	-1.5690***	-1.6690***
	(0.4561)	(0.4962)	(0.4961)	(0.4679)	(0.5551)	(0.5552)	(0.4780)	(0.5937)	(0.5938)
x*Outside	-0.0018***		-0.0018***	-0.0027***		-0.0027***	-0.0042***		-0.0042***
	(0.0005)		(0.0005)	(0.0006)		(0.0006)	(0.0008)		(0.0008)
ΔElev*Outside		0.0416***	0.0424***		0.0015	0.0039		0.0083	0.0103
		(0.0070)	(0.0070)		(0.0106)	(0.0106)		(0.0118)	(0.0118)
N	30549	30549	30549	30549	30549	30549	30549	30549	30549
3. RF log(income)									
outside	0.0236**	0.0020	0.0025	0.0095	0.0137	0.0109	0.0210**	0.0251**	0.0235**
	(0.0095)	(0.0106)	(0.0106)	(0.0094)	(0.0107)	(0.0107)	(0.0098)	(0.0116)	(0.0116)
x*Outside	-0.0001***		-0.0001***	-0.0001***		-0.0001***	-0.0001***		-0.0001***
	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)
ΔElev*Outside		0.0009***	0.0009***		-0.0001	-0.0001		-0.0001	-0.0001
		(0.0002)	(0.0002)		(0.0003)	(0.0003)		(0.0003)	(0.0003)
N	30549	30549	30549	30549	30549	30549	30549	30549	30549
4. IV log(income)									
sewer %	0.0303***	0.0152***	0.0252***	0.0197***	-0.0070	0.0196***	0.0098***	-0.0160*	0.0094***
	(0.0082)	(0.0048)	(0.0046)	(0.0047)	(0.0070)	(0.0047)	(0.0036)	(0.0097)	(0.0035)
N	30549	30549	30549	30549	30549	30549	30549	30549	30549
F	8.430	15.77	14.94	15.77	5.220	10.56	21.10	4.418	14.31
Elevation	Y	Y	Y	Y	Y	Y	Y	Y	Y
π-bins	Y	Y	Y	Y	Y	Y	Y	Y	Y
x	Y	Y	Y						
seg$\times$x				Y	Y	Y			
π-bins$\times$x							Y	Y	Y

Note: Robust standard errors in parentheses. Significance stars * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Sewers and literacy rate, Universe

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1. OLS									
sewer %	0.0000	0.0000	0.0000	-0.0000	-0.0000	-0.0000	0.0002***	0.0002***	0.0002***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0000)	(0.0000)	(0.0000)
N	53747	53747	53747	53747	53747	53747	53747	53747	53747
2. First stage									
outside	-0.7829**	-0.5585	-0.5482	-1.4033***	-0.4658	-0.5616	-1.0052***	-0.3937	-0.5832
	(0.3409)	(0.3841)	(0.3841)	(0.3472)	(0.4264)	(0.4266)	(0.3573)	(0.4570)	(0.4577)
x*Outside	-0.0050***		-0.0050***	-0.0055***		-0.0054***	-0.0064***		-0.0064***
	(0.0004)		(0.0004)	(0.0005)		(0.0005)	(0.0006)		(0.0006)
ΔElev*Outside		-0.0142**	-0.0095		-0.0369***	-0.0330***		-0.0184*	-0.0162
		(0.0072)	(0.0073)		(0.0093)	(0.0093)		(0.0102)	(0.0103)
N	53747	53747	53747	53747	53747	53747	53747	53747	53747
3. RF literacy rate									
outside	0.0046*	0.0029	0.0030	0.0020	0.0042	0.0041	0.0019	0.0031*	0.0030*
	(0.0027)	(0.0029)	(0.0029)	(0.0024)	(0.0038)	(0.0038)	(0.0012)	(0.0016)	(0.0016)
x*Outside	-0.0000**		-0.0000**	-0.0000**		-0.0000**	-0.0000*		-0.0000*
	(0.0000)		(0.0000)	(0.0000)		(0.0000)	(0.0000)		(0.0000)
ΔElev*Outside		0.0001*	0.0001**		-0.0001	-0.0001		-0.0000	-0.0000
		(0.0000)	(0.0000)		(0.0001)	(0.0001)		(0.0000)	(0.0000)
N	53747	53747	53747	53747	53747	53747	53747	53747	53747
4. IV literacy rate									
sewer %	0.0014**	-0.0045**	0.0013**	0.0007*	0.0006	0.0008**	0.0004	-0.0005	0.0005
	(0.0006)	(0.0022)	(0.0006)	(0.0004)	(0.0008)	(0.0003)	(0.0003)	(0.0010)	(0.0003)
N	53747	53747	53747	53747	53747	53747	53747	53747	53747
F	88.72	5.835	59.86	83.58	17.79	60.75	73.04	5.024	49.66
Elevation	Y	Y	Y	Y	Y	Y	Y	Y	Y
π-bins	Y	Y	Y	Y	Y	Y	Y	Y	Y
x	Y	Y	Y						
seg$\times$x				Y	Y	Y			
π-bins$\times$x							Y	Y	Y

Note: Robust standard errors in parentheses. Significance stars * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Summary

- A 1% increase in sewer share gives about a 3% increase in population density in the Universe. This is about the same for both instruments, and double or triple the OLS effect. This conclusion has been robust to different sampling rules
- No effect on income or literacy.

Estimating an Average Treatment Effect I

- Our TSLS estimate is difficult to interpret as a LATE because we have a continuous instrument, e.g. Kasy [2014], Imbens and Newey [2009].
- At the **parcel** level, treatment is binary, and we have the following parcel level model of treatment,

$$\begin{aligned} Y_{ij}(1) &= X_{ij}'\beta_1 + U_{ij}(1), \\ Y_{ij}(0) &= X_{ij}'\beta_0 + U_{ij}(0), \\ D_{ij} &= 1\{p(W_{ij}) \geq V_{ij}\}, \end{aligned}$$

  $i \sim$ parcel, $j \sim$ tract, $p(W_{ij}) = \Pr(D_{ij} = 1 | W_{ij})$ is the propensity score at parcel level, and V_{ij} is unobserved cost or resistance to treatment at the parcel.

Estimating an Average Treatment Effect II

- The local IV regression, MTE and tract conditional average treatment effect are

$$
\begin{aligned}
Y_{ij} &= X_{ij}'\beta_0 + p(W_{ij})X_{ij}'(\beta_1 - \beta_0) + \phi(p(W_{ij})) + U_{ij} \\
\implies MTE(x, v) &\equiv E[Y_{ij}(1) - Y_{ij}(0) | X_{ij} = x, V_{ij} = v] \\
&= x'(\beta_1 - \beta_0) + \phi'(v) \\
\implies CATE(\bar{X}_j) &= \bar{X}_j'(\beta_1 - \beta_0) + \int_0^1 \phi'(v) dv.
\end{aligned}
$$

  This is completely conventional, see Heckman and Vytlacil [2005].

Estimating an Average Treatment Effect III

- Estimate parcel level MTE model using tract level data and a small variance approximation,
- Express the parcel-level characteristics as the sum of tract level average and the residuals:

$$W_{ij} = \begin{bmatrix} \bar{X}_j + \sigma\epsilon_{ij}^X \\ \bar{Z}_j + \sigma\epsilon_{ij}^Z \end{bmatrix} = \bar{W}_j + \sigma\epsilon_{ij},$$

where σ^2 is a scaling factor and

$$\epsilon_{ij} = [\epsilon_{ij}^X, \epsilon_{ij}^Z],\ E(\epsilon_{ij}|j) = 0,\ Var(\epsilon_{ij}|j) = R_j.$$

Estimating an Average Treatment Effect IV

- Approximate **parcel** level model with **tract** level data,

$$
\begin{aligned}
p_j &\equiv E[D_{ij}|j] \\
&= p(\bar{W}_j) + \frac{\sigma^2}{2} tr\left(\nabla^2 p(\bar{W}_j) \cdot R_j\right) + O(\sigma^3) \\
\bar{Y}_j &= \bar{X}_j' \beta_0 + p(\bar{W}_j) \bar{X}_j (\beta_1 - \beta_0) + \\
&\quad \sigma^2 \left[\nabla p(\bar{W}_j) R_j^{WX} + \frac{1}{2} tr\left(\nabla^2 p(\bar{W}_j) \cdot R_j\right) \bar{X}_j' \right] (\beta_1 - \beta_0) \\
&\qquad + \phi(p(\bar{W}_j)) + \phi'(p(\bar{W}_j)) \frac{\sigma^2}{2} tr\left(\nabla^2 p(\bar{W}_j) \cdot R_j\right) \\
&\qquad + \phi''(p(\bar{W}_j)) \sigma^2 \nabla p(\bar{W}_j) R_j (\nabla p(\bar{W}_j))' + O_p(\sigma^3) + \eta_j,
\end{aligned}
$$

where we observe R_j at the 30m^2 grid cell and use this to measure the parcel level covariance of $W = [X, Z]$. Estimate with GMM. We assume a linear probability model in first stage, and $\beta_1 = \beta_0$.

Table: Average treatment effects

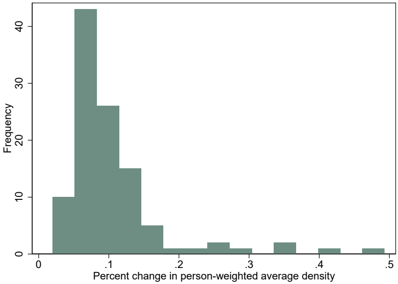
	(1)	(2)	(3)
TSLS	0.0609	0.0064	0.606
	(0.0060)	(0.0158)	(0.0059)
ATE	0.0509	0.0448	0.0556
	(?.????)	(?.????)	(?.????)
F	73.54	5.001	49.99
Elevation	Y	Y	Y
π-bins	Y	Y	Y
pi-bins $\times x$	Y	Y	Y
$z =$outside	Y	Y	Y
$z =$outside $\times x$	Y	.	Y
$z =$outside $\times \Delta h$	.	Y	Y

Average treatment effects turn out to be pretty close to TSLS.

How important are sewers? v1.0

- Add sewer connections for 1% of people to a city.
- Start with the densest census tract first, and work down to less dense tracts.
- Assume each 1% increase in sewer connections increases tract population by 3%.
- This gives a 3% increase in population
- Compare: (1) Baum-Snow [2007] finds that each radial interstate highway decreased the density of US central cities by 9%. (2) Baum-Snow et al. [2017] find that radial highways in China have no impact on total population and lead to a 4% decline in central city population density.

The effect of sewers on city average density (person weighted) is much larger,

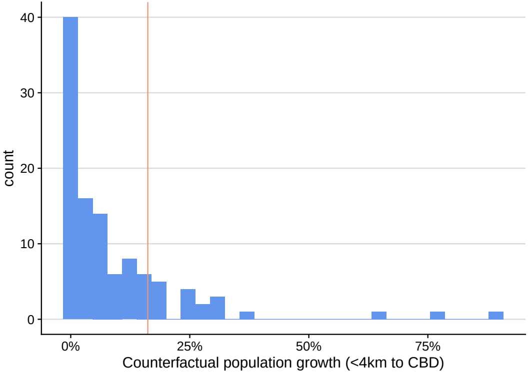


- 1% of sewer connection often results in a 10% increases in person weighted density.
- With a 5% agglomeration effect, this is 0.5% increase in city average wage.
- ...plus whatever wage increase is experienced by the 3% of new residents.

How important are sewers? v2.0

From Tsivanidis [2019], the Transmilenio BRT allows about 18% of the population of Bogota to access the CBD. How important is this compared to providing 100% sewer access within 4k of CBD?

- Complete the sewer network for all tracts with centroids within 4km of CBD.
- Assume each 1% increase in sewer connections increases tract population by 3% holding city population constant.
- Calculate share of city population that gains access to CBD because of this intervention.



- Histogram showing change in % near CBD by city.
- There are many cities where finishing the sewer network in the central city will have as big an impact on access to the center as a world class BRT system.
- This suggests that labor market benefits of sewer systems are sometimes of similar magnitude to those of a BRT, on top of direct benefits.

Conclusion I

- We've estimated the effects of sewer access on population density in a sample of developing world cities.
- We have two distinct identification strategies.
- At 3%, the average effect seems large, both absolutely, and in comparison with (nearly) comparable estimates for highways.
- Resorting in response to sewer access is unimportant.
- There is a lot of cross-country heterogeneity.
- TBD. Work out econometrics that allow for heterogenous treatment effects.

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