Urban costs around the world

Jordan Rosenthal-Kay
Federal Reserve Bank of San Francisco

10 January 2026

STEG, Theme 4 Workshop – Nairobi, Kenya

How do urban costs inhibit economic development?

Urban form varies around the world: dev'ping cities shorter, wider, denser

Jedwab (2021), Ahlfeldt et al. (2024)

Driven by the level of development (demand) or differences in urban costs (supply)

Urban costs: constraints on building and transportation technology

- Limit cities' sizes and absorptive capacity
- Three margins: building up, out, and commuting costs

How do urban costs inhibit economic development?

Urban form varies around the world: dev'ping cities shorter, wider, denser

Jedwab (2021), Ahlfeldt et al. (2024)

Driven by the level of development (demand) or differences in urban costs (supply)

Urban costs: constraints on building and transportation technology

- Limit cities' sizes and absorptive capacity
- Three margins: building up, out, and commuting costs

What are the urban costs faced by cities around the world?

What would the gains be if urban costs were reduced?

Answering these questions in a data-poor environment

Answering questions of this scope requires leveraging data that is available globally

- Classical urban theory + global satellite data to analyze urban form

Contributions to the literature

Answering these questions in a data-poor environment

Answering questions of this scope requires leveraging data that is available globally

- Classical urban theory + global satellite data to analyze urban form

Developing world cities build out, not up, and have higher commuting costs

- Sufficient stat: the urban cost elasticity. 35% larger in dev'ping cities vs. rich world cities

Contributions to the literature

Answering these questions in a data-poor environment

Answering questions of this scope requires leveraging data that is available globally

- Classical urban theory + global satellite data to analyze urban form

Developing world cities build out, not up, and have higher commuting costs

- Sufficient stat: the urban cost elasticity. 35% larger in dev'ping cities vs. rich world cities

Spatial model (system-of-cities + urbanization) to assess aggregate impact of high urban costs

- Lowering urban costs to U.S. level raises welfare by 66% in dev'ping nations

Contributions to the literature

Answering these questions in a data-poor environment

Answering questions of this scope requires leveraging data that is available globally

- Classical urban theory + global satellite data to analyze urban form

Developing world cities build out, not up, and have higher commuting costs

- Sufficient stat: the urban cost elasticity. 35% larger in dev'ping cities vs. rich world cities

Spatial model (system-of-cities + urbanization) to assess aggregate impact of high urban costs

- Lowering urban costs to U.S. level raises welfare by 66% in dev'ping nations

Scope for policy: urban road paving

- Road paving *can be* a cost effective policy, but targeting matters

Contributions to the literature

Answering these questions in a data-poor environment

Answering questions of this scope requires leveraging data that is available globally

- Classical urban theory + global satellite data to analyze urban form

Developing world cities build out, not up, and have higher commuting costs

- Sufficient stat: the urban cost elasticity. 35% larger in dev'ping cities vs. rich world cities

Spatial model (system-of-cities + urbanization) to assess aggregate impact of high urban costs

- Lowering urban costs to U.S. level raises welfare by 66% in dev'ping nations

Scope for policy: urban road paving

- Road paving *can be* a cost effective policy, but targeting matters

High urban costs hinder climate change adaptation

- Simulate climate damages to nations' agricultural sectors – $2\times$ urban cost elasticity, climate damages $\uparrow$ 8%

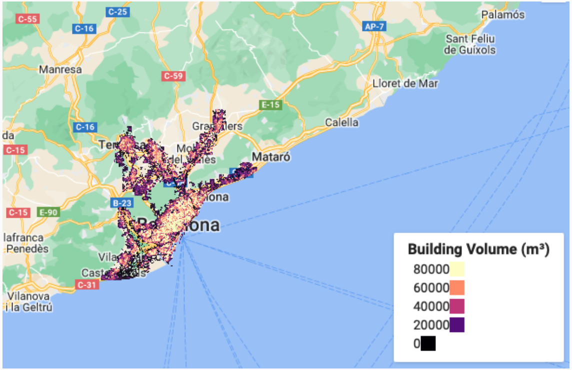
Contributions to the literature

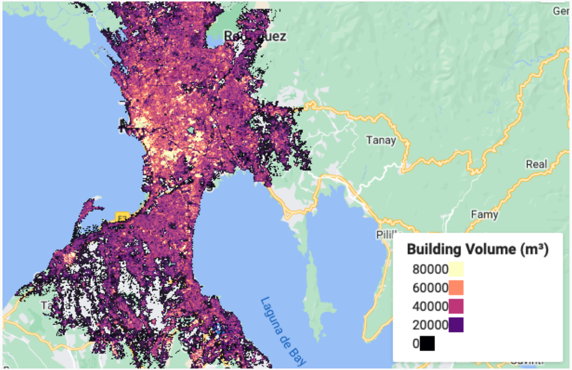
Road map

1. What do we know, and why might we think urban costs vary around the world?
   - Data: Global Human Settlement Layer (GHSL), remote-sensed boundaries for cities of >50K persons
   - Built volume data at 100m $\times$ 100m
2. Quantitative model of an urban system
   - Link urban form to urban costs
   - Fully GE: think carefully about measurement, & capture gains from reallocation in counterfactuals
3. Model estimation with geospatial data
   - Recover components of urban costs with geospatial data and model-consistent regressions
4. How important are urban costs?
   - Counterfactual: measure gains from lowering urban costs to the U.S. level
   - Explore urban road paving as a policy intervention

What do we know about cities around the world?

A tale of two cities: Barcelona, Spain and Manila, Philippines





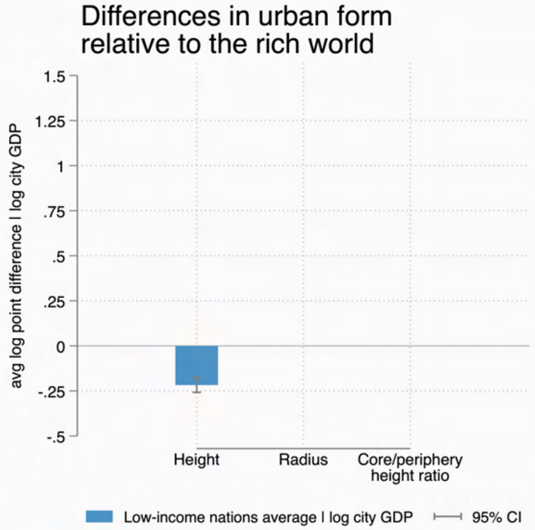
In 2015, GDP of both $\approx$ \$100 billion, GDP/cap Spain: \$25,000, Philippines: \$3,000.

Manila: shorter, wider, but more packed in

What do we know

Conditional on city income, compared rich-world cities, cities in developing nations...

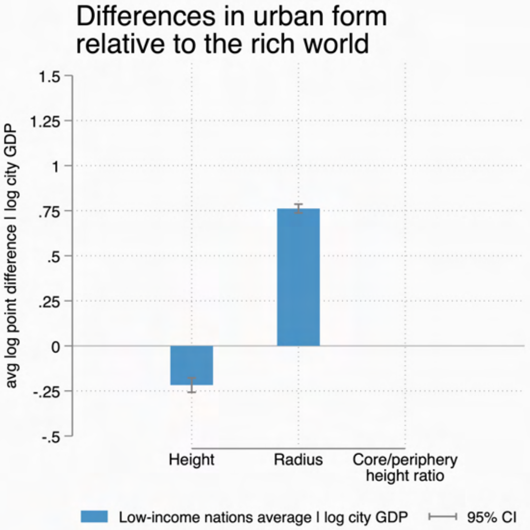
1. are on avg. 22% shorter,



What do we know

Conditional on city income, compared rich-world cities, cities in developing nations...

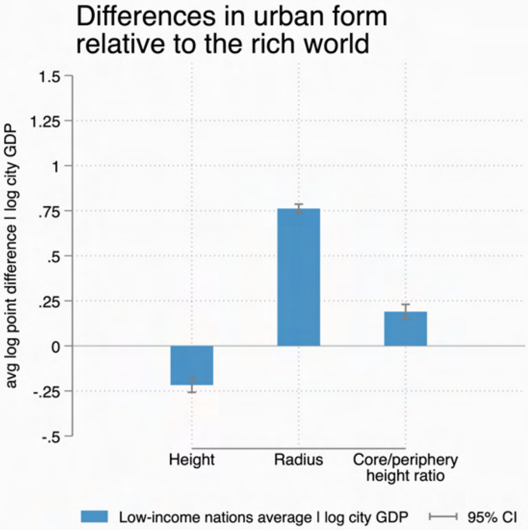
1. are on avg. 22% shorter,
2. but are over 75% wider,



What do we know

Conditional on city income, compared rich-world cities, cities in developing nations...

1. are on avg. 22% shorter,
2. but are over 75% wider,
3. and average height in the core *relative* to the periphery is 19% taller

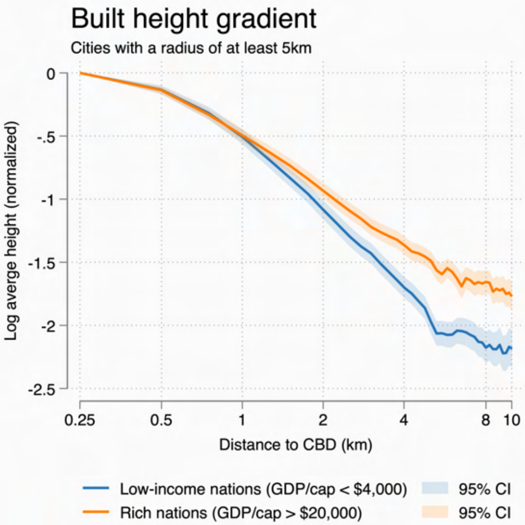


What do we know

Conditional on city income, compared rich-world cities, cities in developing nations...

1. are on avg. 22% shorter,
2. but are over 75% wider,
3. and average height in the core *relative* to the periphery is 19% taller
4. and the average city has a skyline that is 33% steeper

Cross-country regressions   Cross-country figures



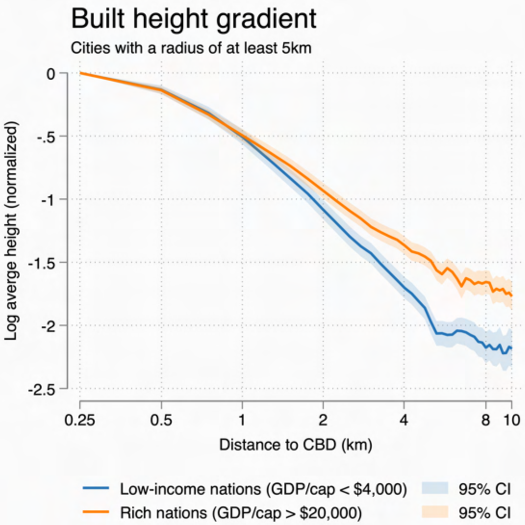
What do we know

Conditional on city income, compared rich-world cities, cities in developing nations...

1. are on avg. 22% shorter,
2. but are over 75% wider,
3. and average height in the core *relative* to the periphery is 19% taller
4. and the average city has a skyline that is 33% steeper

Cross-country regressions Cross-country figures

Developing cities build out, not up, but crowd mass in their downtowns



A quantitative model of cities

A quantitative framework to link cities' internal structure to the macroeconomy

Mass L households choose among cities i (or ag. sector) to live and work, and where to live (x, ϕ) within cities.

Households earn wage w_i, consume traded goods $\{c_j\}$ and floorspace h, and pay **commuting costs** in utils

Monocentric cities with endogenous radius X_i.

Will only study symmetric allocations along arcs ϕ

A continuum of identical developers construct **urban land** πX_i^2 and **floorspace** $H_i(x)$.

Cities produce traded urban varieties, agricultural sector produces a freely traded numeraire good.

A quantitative framework to link cities' internal structure to the macroeconomy

Mass L households choose among cities i (or ag. sector) to live and work, and where to live (x, ϕ) within cities.

Households earn wage w_i, consume traded goods $\{c_j\}$ and floorspace h, and pay **commuting costs** in utils

Monocentric cities with endogenous radius X_i.

Will only study symmetric allocations along arcs ϕ

A continuum of identical developers construct **urban land** πX_i^2 and **floorspace** $H_i(x)$.

Cities produce traded urban varieties, agricultural sector produces a freely traded numeraire good.

Each household ν solves...

$$\max_{x,i,\{c_j\},h} \; U(x,i,\{c_j\},h) \; \underbrace{\epsilon_i(\nu)}_{\sim \text{Frechet}(1,\varepsilon)}$$

$$U \propto \underbrace{A_i(x)}_{\substack{\text{amenities/}\\ \text{com. costs}}} (C)^{\alpha} (\underbrace{\psi^H}_{\text{qual. adj.}} h)^{\beta} (c_0)^{1-\alpha-\beta}$$

$$C = \text{CES}(c_j) \text{ w. eos } \sigma$$

$$\text{s.t.} \sum_j p_{ji} c_j + c_0 + q_i(x) h \le w_i$$

A quantitative framework to link cities' internal structure to the macroeconomy

Mass L households choose among cities i (or ag. sector) to live and work, and where to live (x, ϕ) within cities.

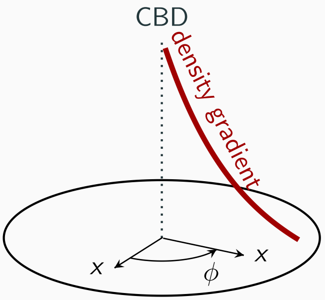
Households earn wage w_i, consume traded goods $\{c_j\}$ and floorspace h, and pay **commuting costs** in utils

Monocentric cities with endogenous radius X_i.

Will only study symmetric allocations along arcs ϕ

A continuum of identical developers construct **urban land** πX_i^2 and **floorspace** $H_i(x)$.

Cities produce traded urban varieties, agricultural sector produces a freely traded numeraire good.



A quantitative framework to link cities' internal structure to the macroeconomy

Mass L households choose among cities i (or ag. sector) to live and work, and where to live (x, ϕ) within cities.

Households earn wage w_i, consume traded goods $\{c_j\}$ and floorspace h, and pay **commuting costs** in utils

Monocentric cities with endogenous radius X_i.

- Will only study symmetric allocations along arcs ϕ

A continuum of identical developers construct **urban land** πX_i^2 and **floorspace** $H_i(x)$.

Cities produce traded urban varieties, agricultural sector produces a freely traded numeraire good.

Cities produce varieties traded w. iceberg costs $\delta_{ij} \geq 1$,

$$y_i = Z_i^y L_i, \quad Z_i^y = \underbrace{\bar{Z}_i^y}_{\text{fixed}} \underbrace{\left(\frac{L_i}{\pi X_i^2}\right)^{\zeta}}_{\text{agglomeration}}$$

Ag sector,

$$y_0 = \bar{Z}_0^y \left(L_0\right)^{1-\mu} \left(T_0\right)^{\mu}$$

Urban technology: τ_i, γ_i, ρ_i

Cities' amenities supply function:

$$A_i(x) = \underbrace{\bar{A}_i}_{\substack{\text{citywide} \\ \text{amenity}}} \times \underbrace{(x)^{-\tau_i}}_{\substack{\text{location-specific} \\ \text{commuting costs}}}$$

A continuum of identical developers build urban land and floorspace, generating supply curves,

$$\underbrace{H_i(x) = \frac{Z_i^H}{\psi^H} q_i(x)^{\gamma_i},}_{\substack{\text{floorspace supply} \\ \text{per unit land}}} \quad \underbrace{\pi X_i^2 = \frac{Z_i^X}{\psi^X} r_i(X_i)^{\rho_i}}_{\text{land supply}}$$

τ_i, commuting cost elasticity: transportation infrastructure

γ_i, floorspace supply elasticity: verticial building constraints (bedrock, regulation...)

ρ_i, land supply elasticity: increasing marginal costs to weave land into the urban fabric

Los Angeles: build into the Hollywood Hills; Singapore: land reclamation Microfoundation

ψ^H, ψ^X - quality adjustment terms, assumed constant within a nation

Equilibrium

Primitives,

- Urban development: technology parameters $\{\boldsymbol{\tau_i}, \boldsymbol{\gamma_i}, \boldsymbol{\rho_i}\}$ & fundamentals $\{\bar{A}_i, Z_i^H, Z_i^X, \psi^H, \psi^X\}$
- Urban production: TFP $\{\bar{Z}_i^y\}$, agglomeration strength ζ, & trade costs $\{\delta_{ij}\}$
- Households preference parameters $\{\alpha, \beta, \sigma, \varepsilon\}$
- Agricultural production: land share in production, μ

Equilibrium

Primitives,

- Urban development: technology parameters $\{\boldsymbol{\tau_i}, \boldsymbol{\gamma_i}, \boldsymbol{\rho_i}\}$ & fundamentals $\{\bar{A}_i, Z_i^H, Z_i^X, \psi^H, \psi^X\}$
- Urban production: TFP $\{\bar{Z}_i^y\}$, agglomeration strength ζ, & trade costs $\{\delta_{ij}\}$
- Households preference parameters $\{\alpha, \beta, \sigma, \varepsilon\}$
- Agricultural production: land share in production, μ

An equilibrium is a population distribution across locations $\{L_i\}$, across sites in cities $\{L_i(x)\}$, urban radii $\{X_i\}$, floorspace prices $\{q_i(x)\}$, land rents $\{r_i(x)\}$, goods prices $\{p_i\}$, wages $\{w_i\}$, and common urban utility $\{U_i\}$, such that

1. Households, developers, and firms maximize, taking prices as given,
2. Within each city, all households live somewhere + spatial eq'm holds, $U_i(x) = U_i$,
3. Floorspace and goods markets clear
4. Profits: agricultural workers earn their average product, dev't profits accrue to land

Full definition

Existence / uniqueness

The urban cost elasticity combines all elements of the urban technology

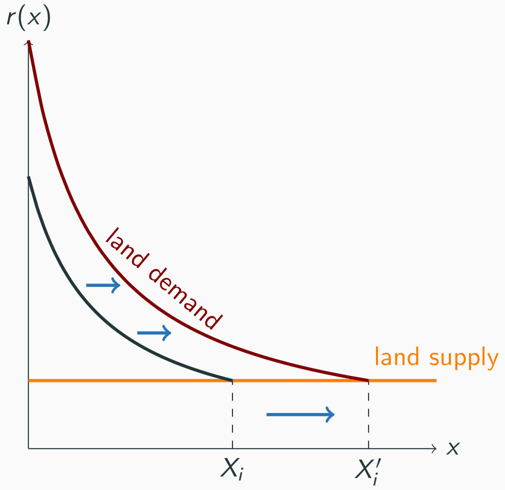
The urban cost elasticity,

$$\kappa_i \equiv \frac{1}{1+\rho_i}\frac{\beta}{1+\gamma_i} + \frac{\rho_i}{1+\rho_i}\frac{\tau_i}{2}$$

Elasticity of city indirect utility to city population, holding wages and traded goods prices fixed.

% increase in consumption utility required to offset the costs from a 1% increase in city population. (Combes et al., 2019)

$$\underbrace{\rho_i \to \infty}_{\text{land supply is perfectly elastic}} \quad \Longrightarrow \quad \underbrace{\frac{\tau_i}{2}}_{\text{all congestion from commuting costs}}$$



The urban cost elasticity combines all elements of the urban technology

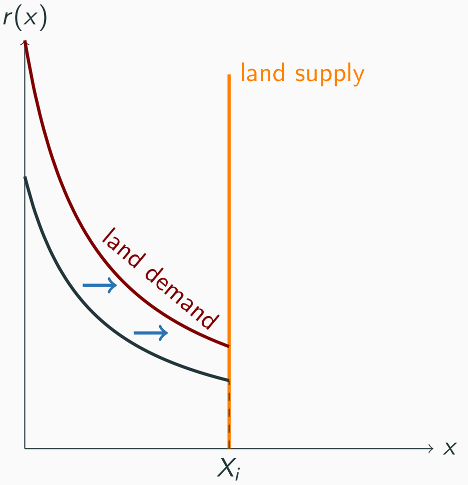
The urban cost elasticity,

$$\kappa_i \equiv \frac{1}{1+\rho_i}\frac{\beta}{1+\gamma_i} + \frac{\rho_i}{1+\rho_i}\frac{\tau_i}{2}$$

Elasticity of city indirect utility to city population, holding wages and traded goods prices fixed.

% increase in consumption utility required to offset the costs from a 1% increase in city population. (Combes et al., 2019)

$$\underbrace{\rho_i \to 0}_{\text{land supply is perfectly inelastic}} \implies \underbrace{\frac{\beta}{1+\gamma_i}}_{\text{all congestion thru floorspace market}}$$



The urban cost elasticity combines all elements of the urban technology

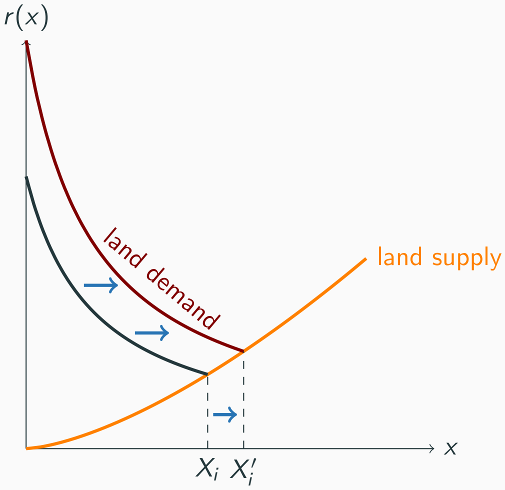
The urban cost elasticity,

$$\kappa_i \equiv \frac{1}{1+\rho_i}\frac{\beta}{1+\gamma_i} + \frac{\rho_i}{1+\rho_i}\frac{\tau_i}{2}$$

Elasticity of city indirect utility to city population, holding wages and traded goods prices fixed.

% increase in consumption utility required to offset the costs from a 1% increase in city population. (Combes et al., 2019)

generally, just κ_i



Estimating components of the urban technology

Data

Goal: estimate parameters that govern the urban technology,

$$\underbrace{\tau_i}_{\substack{\text{commuting costs} \\ \text{distance elasticity}}} \qquad \underbrace{\gamma_i}_{\substack{\text{floorspace supply} \\ \text{elasticity}}} \qquad \underbrace{\rho_i}_{\substack{\text{land supply} \\ \text{elasticity}}}$$

Data:

- GHSL remote sensed urban agglomerations i of over 50K persons, globally
- Observe built volume distribution within cities, and their physical expansion over time
  - $H_i(x)$ – built height (m), πX_i^2 – built area (km^2)
- $w_i L_i$: local GDP extrapolated from VIIRS nightlights aggregated to match national accounts
- L_i: Gridded population of the world
- geophysical observables (slope, soil, etc)

Data

Goal: estimate parameters that govern the urban technology,

$$\underbrace{\tau_i}_{\text{commuting costs distance elasticity}} \quad \underbrace{\gamma_i}_{\text{floorspace supply elasticity}} \quad \underbrace{\rho_i}_{\text{land supply elasticity}}$$

Moments:

- Building height gradient $\rightarrow -\tau_i \gamma_i$
- Height-income relationship across cities $\rightarrow \gamma_i$
- Time series on area and income within cities $\rightarrow \rho_i$

Taking the model to data – measuring building height gradients

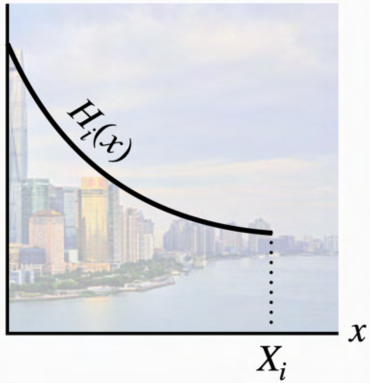
Internal structure,

$$\frac{d \log H_i(x)}{d \log x} = \frac{-\tau_i \gamma_i}{\beta}$$

Skyline gradient depends on:

- Costly for households to build out (τ_i high)
- Cheap for developers to build up (γ_i high)

AMM logic

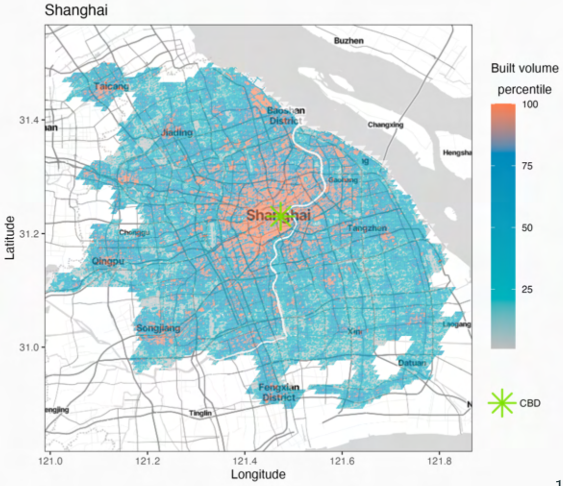


Shanghai's skyline.

Taking the model to data – measuring building height gradients

Data: Global Human Settlement Layer (GHSL)

- $\approx$10,000 cities i of $\geq$50K people
- $H_i(x, \phi)$ (avg height $\times$ built surface) at 100m$\times$100m pixels
- x: distance to Google Maps' downtown
- $\geq$300 million observations



Taking the model to data – measuring building height gradients

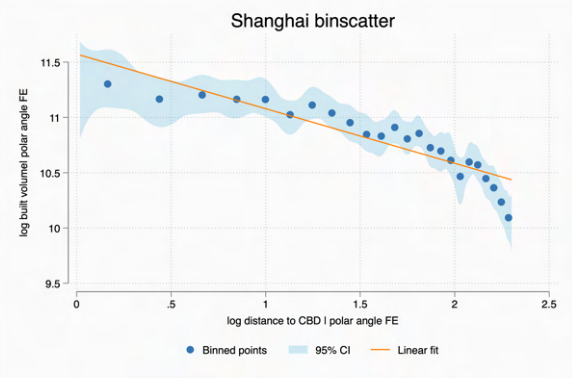
Poisson estimator $-\tau_i\gamma_i/\beta$ for each city,

$$\log H_i(x,\phi) = -\frac{\tau_i\gamma_i}{\beta}\log x + \xi_{i,\phi} + t_i(x)$$

Adjustments,

- reweight to undo rise in observations as $x \uparrow$
- Shrink to country mean (no $\widehat{-\tau_i\gamma_i/\beta} > 0$)

Empirical Bayes' estimator

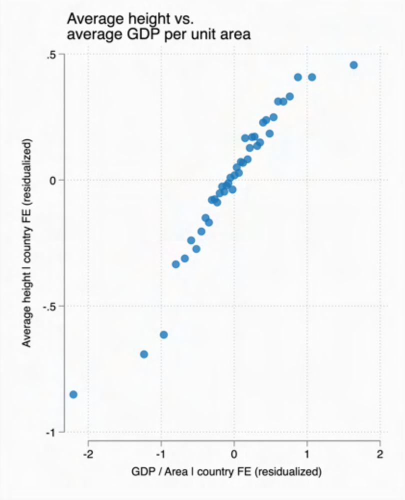


'Binsreg' of log built volume against log x, conditional on polar angle fixed effects, weighted

Measuring the floorspace supply elasticity (γ_i) in the cross-section

Model implied estimating equation,

$$\underbrace{\log \overbrace{\bar{H}_i}^{\substack{\text{total}\\ \text{built volume}}} \Big/ \pi X_i^2}_{\text{average height}} = \frac{\gamma_i}{1+\gamma_i}\left(\log w_i + \log \frac{L_i}{\pi X_i^2}\right) + \varsigma_i$$



'Binsreg' conditional on country fixed effects, in logs

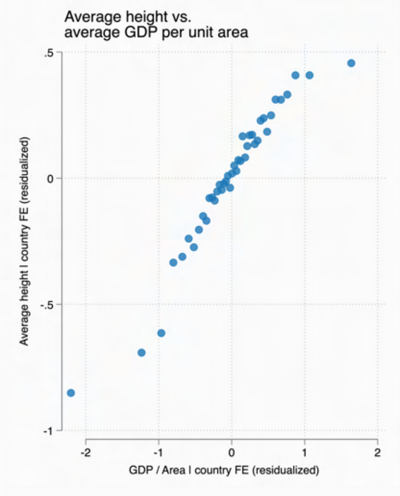
Measuring the floorspace supply elasticity (γ_i) in the cross-section

Model implied estimating equation,

$$\underbrace{\log \overbrace{\bar{H}_i}^{\text{total built volume}} \Big/ \pi X_i^2}_{\text{average height}} = \frac{\gamma_i}{1+\gamma_i}\left(\log w_i + \log \frac{L_i}{\pi X_i^2}\right) + \varsigma_i$$

ς_i contains Z_i^H. $\rightarrow$ Productivity instrument for w_i, $\bar{Z}_i^y$.

- Control for density, country FE, geophysical controls
- IV generated through model inversion Instrument construction



'Binsreg' conditional on country fixed effects, in logs

Measuring the floorspace supply elasticity (γ_i) in the cross-section

Model implied estimating equation,

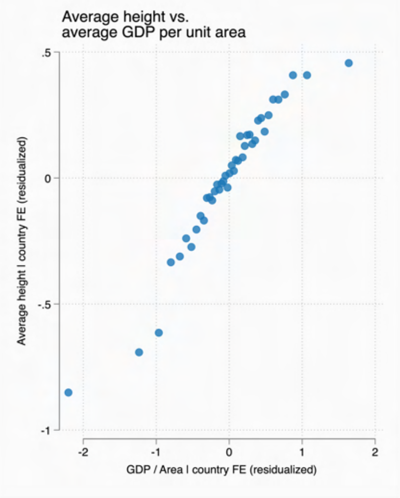
$$\log \underbrace{\overbrace{\bar{H}_i}^{\text{total built volume}} \Big/ \pi X_i^2}_{\text{average height}} = \frac{\gamma_i}{1+\gamma_i}\left(\log w_i + \log \frac{L_i}{\pi X_i^2}\right) + \varsigma_i$$

ς_i contains Z_i^H. $\rightarrow$ Productivity instrument for w_i, $\bar{Z}_i^y$.

- Control for density, country FE, geophysical controls
- IV generated through model inversion Instrument construction

Model $\frac{\gamma_i}{1+\gamma_i} = G_i' \Gamma$.

- G_i: Slope, elevation, soil density, clay, sand, water, WB regulatory measure



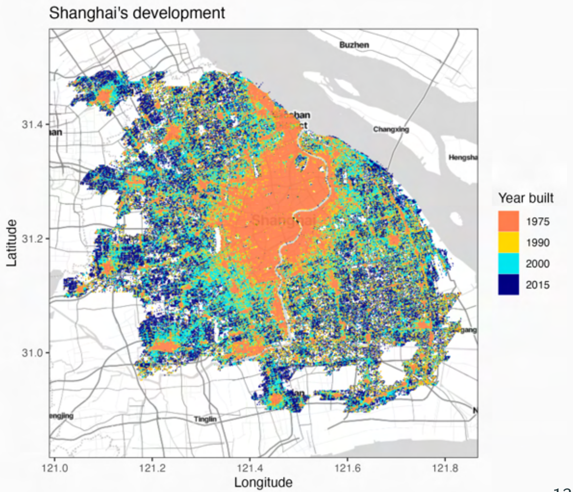
'Binsreg' conditional on country fixed effects, in logs

Measuring the land supply elasticity (ρ_i) using the time series on urban growth

Model implies,

$$\log \pi X_i^2 = \frac{\rho_i}{1+\rho_i} \log w_i L_i + \xi_i$$

where ξ_i contains urban land construction TFP, Z_i^X.



Measuring the land supply elasticity (ρ_i) using the time series on urban growth

Model implies,

$$\log \pi X_i^2 = \frac{\rho_i}{1+\rho_i} \log w_i L_i + \xi_i$$

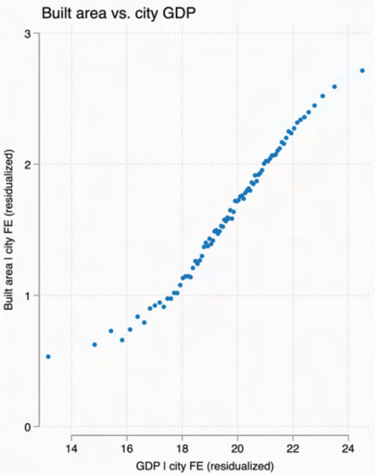
where ξ_i contains urban land construction TFP, Z_i^X.

Identification using the time series:

$$\log \text{area}_{it} = \frac{\rho_i}{1+\rho_i} \log w_{it} L_{it} + \underbrace{\xi_i}_{\substack{\text{city} \\ \text{FE}}} + \underbrace{\xi_{rt}}_{\substack{\text{region-year} \\ \text{FE}}} + e_{it}$$

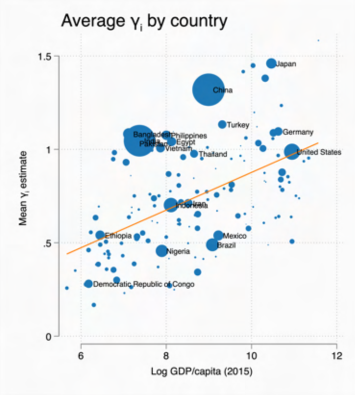
Adjustments,

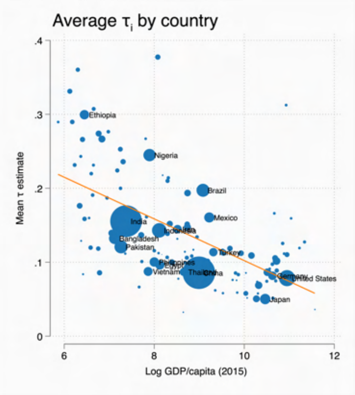
- GDP time series measured with error – instrument with DMSP-OLS nightlights.
- Parameterize $\frac{\rho_i}{1+\rho_i} = G_i' \Omega$.

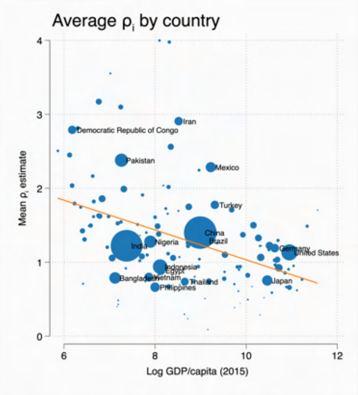


'Binsreg' conditional on city fixed effects, in logs

Estimation results – average $\hat{\gamma}_i, \hat{\tau}_i, \hat{\rho}_i$ vs. nat'l GDP/cap







γ_i coefficient estimates

ρ_i coefficient estimates

USA comparison: Saiz (2010) / Baum-Snow & Han (2024)

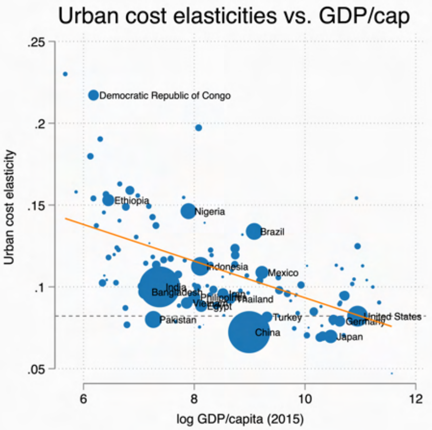
Akbar et al. (2023/2024) comparison

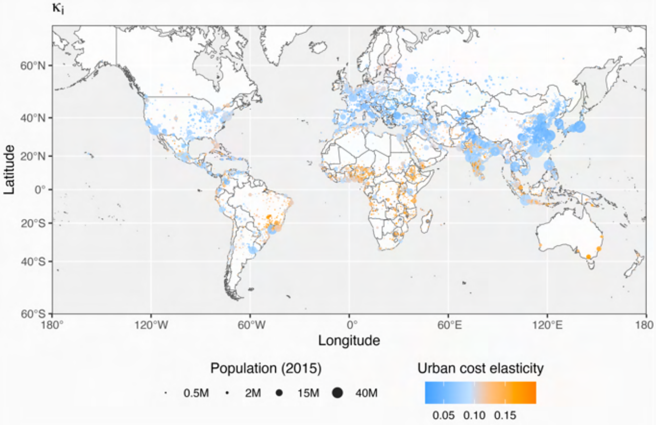
γ_i map

ρ_i map

τ_i map

Urban cost elasticities





Levels of urban costs | Table: regional breakdown | Table: κ_i vs. city size

How do urban costs matter for economic development?

Lowering the urban cost elasticity (κ_i) to the U.S. level

Experiment: lower κ_i so that on average, it is the same as in the U.S.

Goal: assess the stakes, illustrate model mechanisms

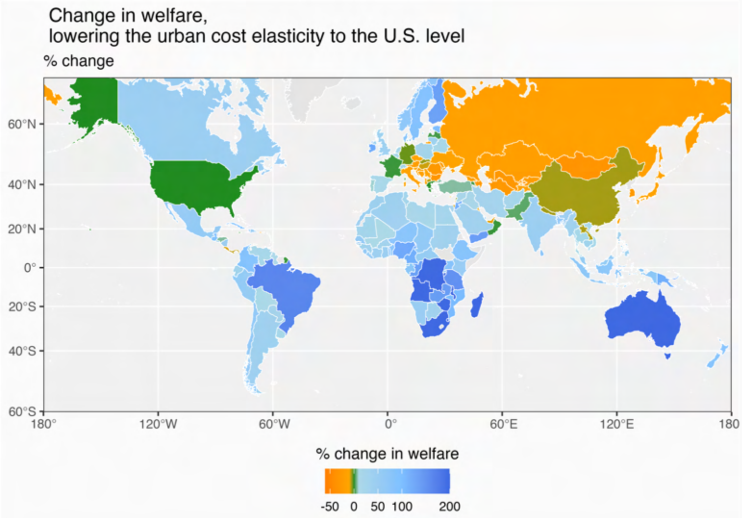
Outcome of interest: Welfare (expected utility) in country n, $\mathcal{W}_n = \left(\sum_i \left(\tilde{A}_i \frac{w_i}{P_i^\alpha}(w_i L_i)^{-\kappa_i}\right)^\varepsilon\right)^{1/\varepsilon}$.

$$\frac{d\mathcal{W}_n}{\mathcal{W}_n} = \text{direct effect} + \text{indirect effect}$$

$$\text{direct effect} = \underbrace{-\sum_i \left(\frac{L_i}{L_n}\right) \kappa_i \log(w_i L_i) \frac{d\kappa_i}{\kappa_i}}_{\text{rotating the `urban cost curve'}}$$

$$\text{indirect effect} = \underbrace{\sum_i \left(\frac{L_i}{L_n}\right) \left(\frac{d(w_i/P_i^\alpha)}{(w_i/P_i^\alpha)} - \kappa_i \frac{d(w_i L_i)}{w_i L_i}\right)}_{\substack{\text{price changes capitalize gains} \\ \text{from spatial reallocation}}}$$

Lowering the welfare effect

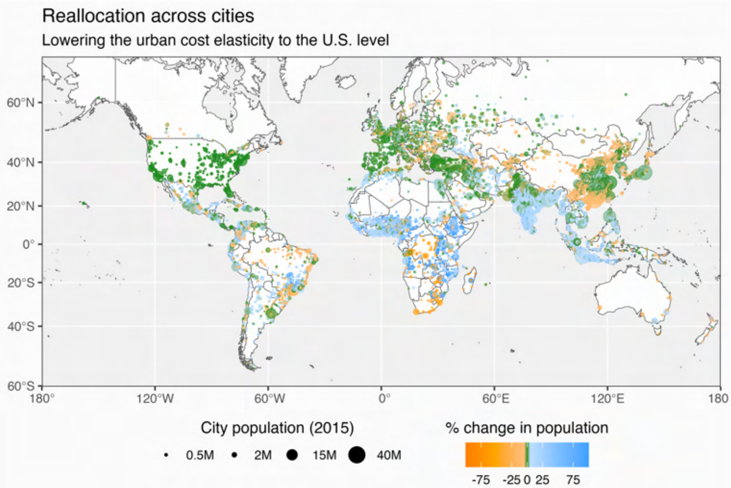


Average welfare gain in developing nations: 66%, 8.8pp increase in urbanization

Scatter: welf, urb

κ_j elements

Lowering the u … welfare effect

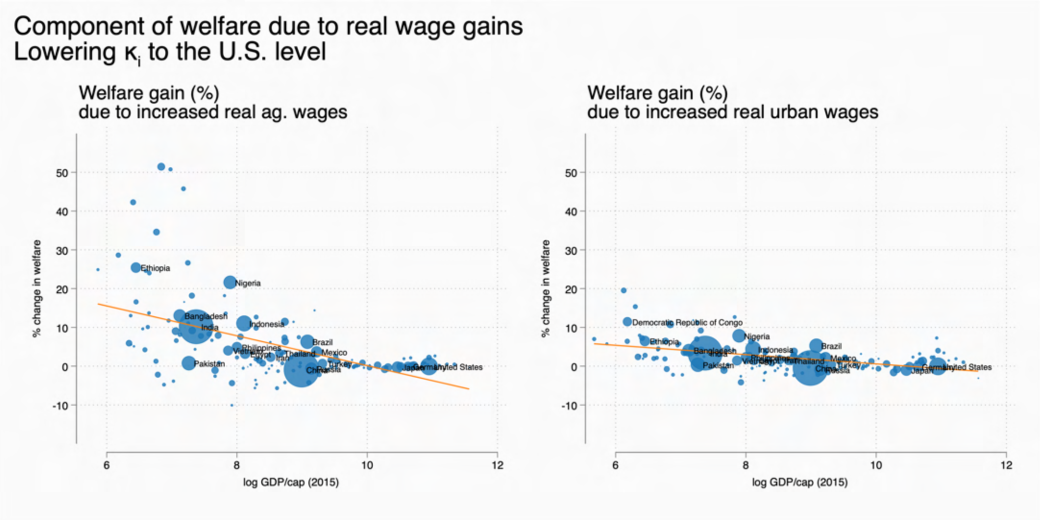


Average welfare gain in developing nations: 66%, 8.8pp increase in urbanization

Scatter: welf, urb

κ_j elements

Lowering the urban cost elasticity (κ_i) to the U.S. level – decomposing the gains



In developing nations: real wage gain in ag. on avg. 18%; real wage gain in urban 4% Lower the level

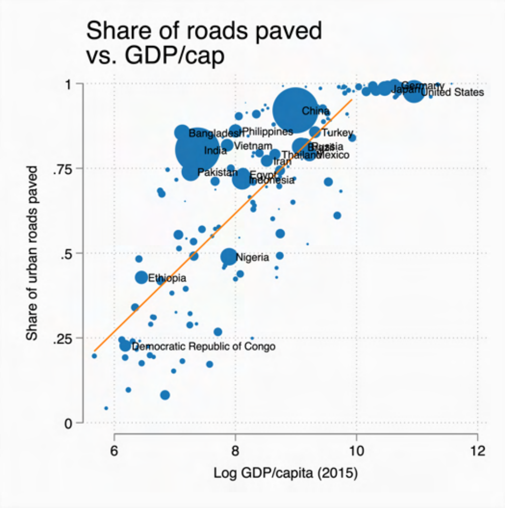
Can urban road paving lower τ_i cost-effectively?

47% of the variation in κ_i is explained by τ_i

partial R^2s

Dev't world: many unpaved urban roads

Data: OpenStreetMap



Can urban road paving lower τ_i cost-effectively?

47% of the variation in κ_i is explained by τ_i

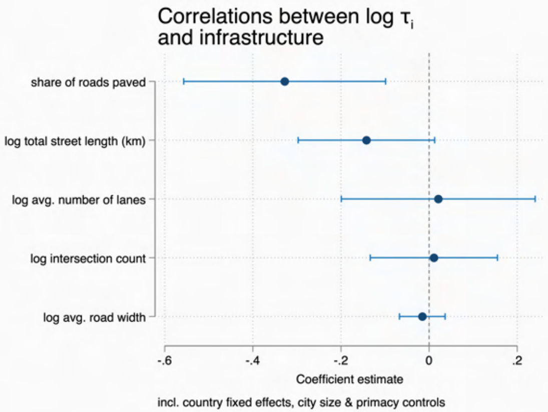
partial R^2s

Dev't world: many unpaved urban roads

Data: OpenStreetMap

$\log \tau_i$ correlates with road char'cs (OSRM)

- conditional on city GDP, country FE



Can urban road paving lower τ_i cost-effectively?

47% of the variation in κ_i is explained by τ_i

partial R^2s

Dev't world: many unpaved urban roads

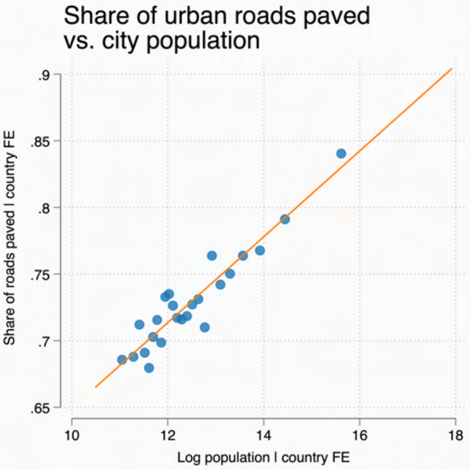
Data: OpenStreetMap

$\log \tau_i$ correlates with road char'cs (OSRM)

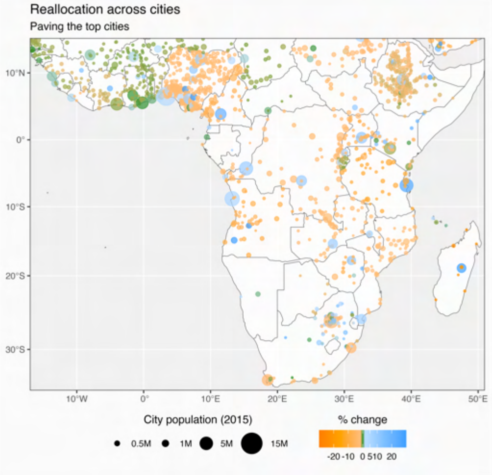
- conditional on city GDP, country FE

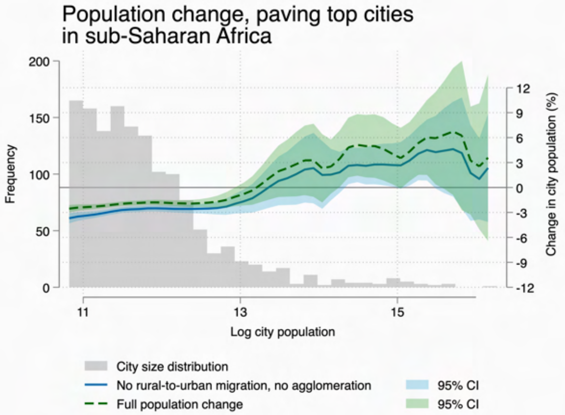
Policy: Pave roads in biggest cities to the U.S. level

- Road paving $\implies \downarrow \kappa_i$
- Fix budget to at most 1% of GDP
- Start with biggest city, work down
- Af. Dev. Bank: \$227,800/km



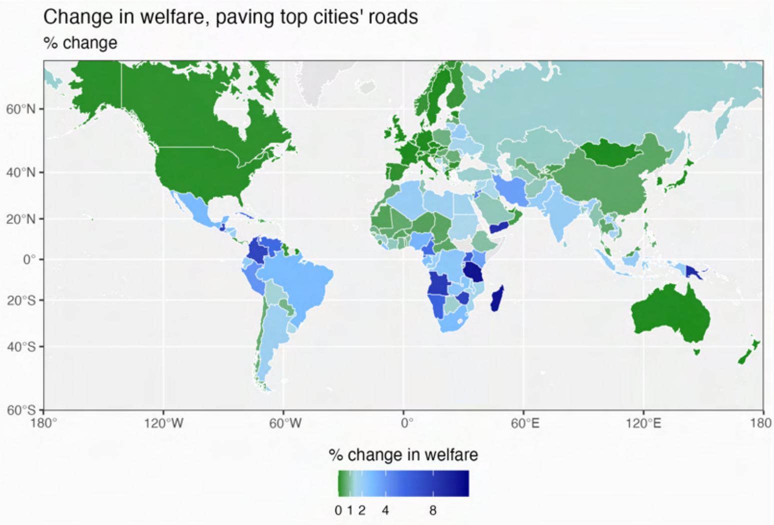
Road paving: reallocates population to larger cities, increases urbanization





Larger cities grow at the expensive of smaller ones, average change in urbanization: 0.5pp Targeted cities

Road paving: ountries



Conclusion: Urban costs matter for development

What have we learned?

- Differences in urban form globally are partially explained by urban costs
- Many developing nations' cities face large urban costs, as measured by the urban cost elasticity
- Reducing urban costs would yield large welfare gains, especially in the developing world
- Urban road paving is an available cost effective policy to lower urban costs
- High urban costs amplify welfare losses from climate change

In short, when it comes to improving cities, the stakes are large!

Thanks!

jordan.rosenthalkay@gmail.com | jrosenthalkay.github.io

Climate change is anticipated to drive rural → urban migration

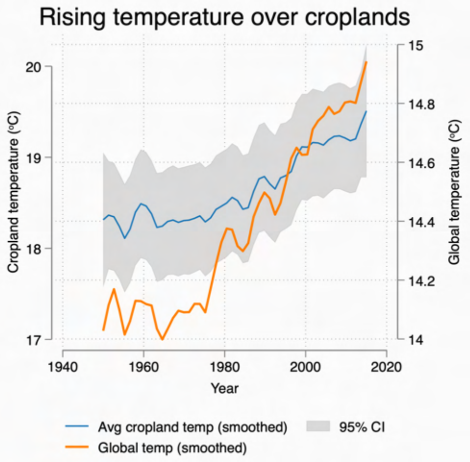
Hypothesis: climate damages primarily in agriculture $\implies$ rural-to-urban migration

Test: do ag. temperature shocks drive urbanization?

Data:

- Average annual temperature over 2015 cropland extent (USGS + Berkeley Earth)
- Share of population urbanized (World Bank)

Back



Climate change is anticipated to drive rural → urban migration

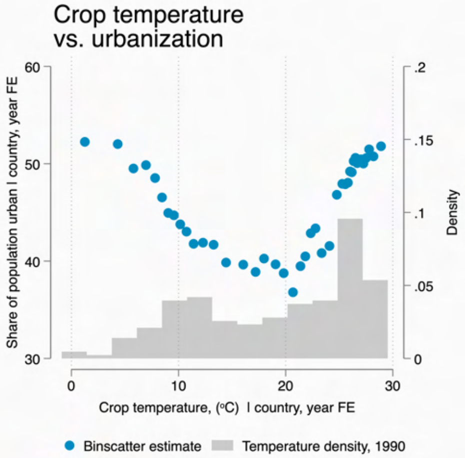
Hypothesis: climate damages primarily in agriculture $\implies$ rural-to-urban migration

Test: do ag. temperature shocks drive urbanization?

Data:

- Average annual temperature over 2015 cropland extent (USGS + Berkeley Earth)
- Share of population urbanized (World Bank)

Back



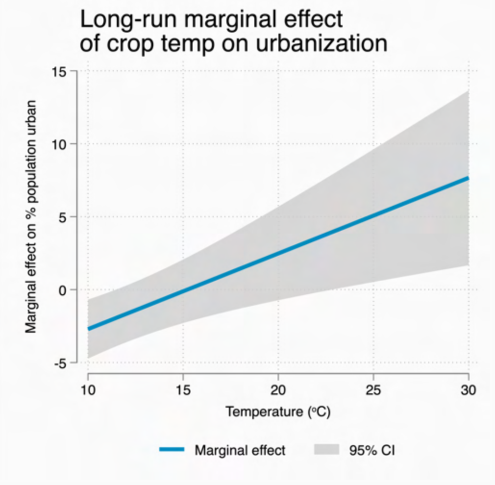
Climate change is anticipated to drive rural $\rightarrow$ urban migration

Test: do ag. temperature shocks drive urbanization?

Estimate nonlinear effect of crop temp. shocks on urbanization:

$$
\begin{aligned}
\text{share urban}_{nt} = \eta_0 \underbrace{T_{nt}}_{\text{crop temp.}} &+ \eta_1 T_{nt}^2 \\
&+ \lambda \text{share urban}_{n,t-1} \\
&+ \chi_0 T_{n,t-1} + \chi_1 T_{n,t-1}^2 \\
&+ \underbrace{\xi_n + \xi_t}_{\text{country + year FE}} + e_{nt}
\end{aligned}
$$

$$\text{long run marginal effect} = \frac{\hat{\eta}_0 + 2\hat{\eta}_1 T_{it}}{1 - \hat{\lambda}}$$



Climate change is anticipated to drive rural → urban migration

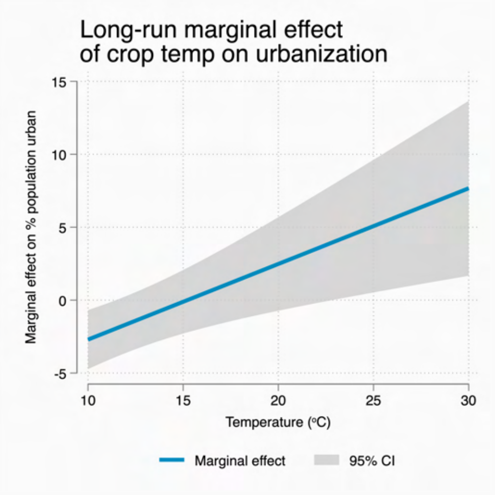
Counterfactual: simulate 1.5° ↑ global temp

- Estimate pattern scaling ς_n

$$T_{nt} = \varsigma_n \text{Global temp}_t + \xi_n + e_{nt}$$

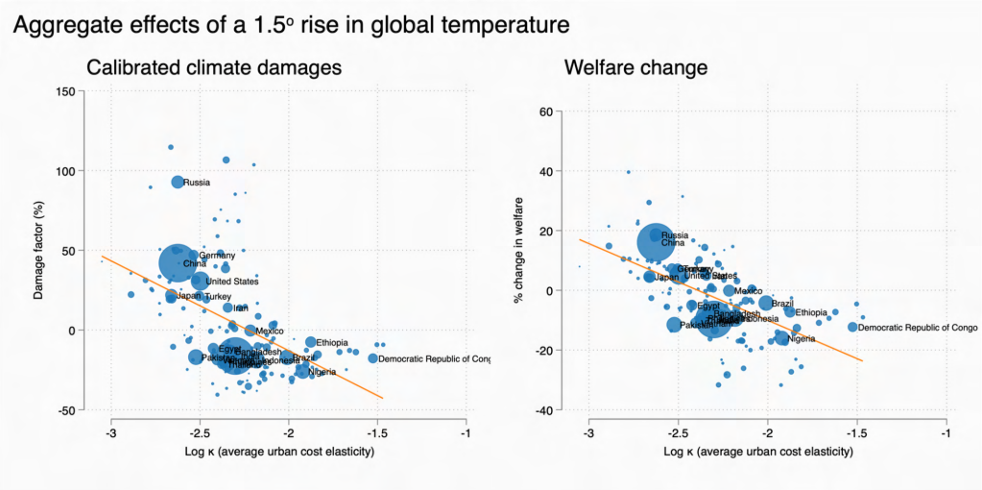
- Map ΔT_{nt} to model parameters with a damage function peaking at 19.9° (Conte et al., 2019)

$$\underbrace{A_0(T_{nt}), \quad Z_0^y(T_{nt})}_{\text{ag. amenity and TFP damages}}$$



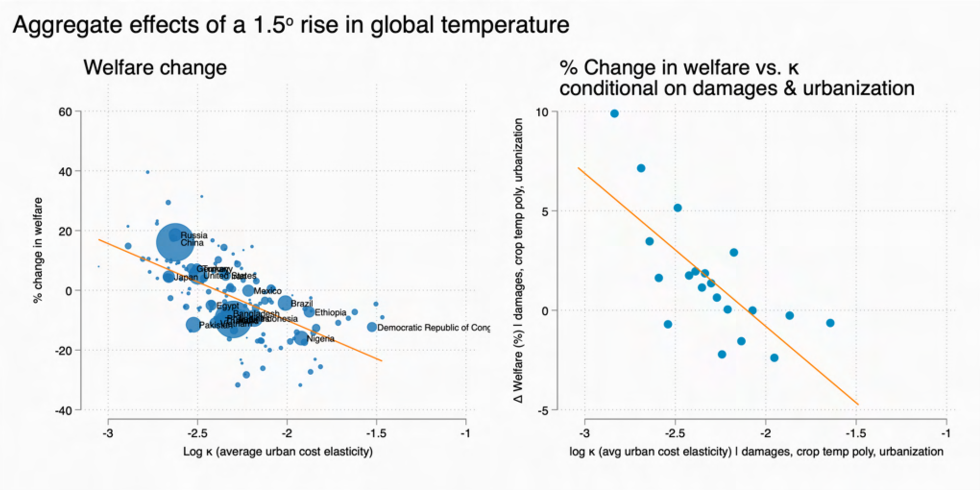
Back

High urban costs amplify losses under climate change



Countries w/ cities least able to scale face highest climate damages

High urban costs amplify losses under climate change



Countries w/ cities least able to scale face highest climate damages

Conditional $\frac{\partial \text{Welf}}{\partial \log \kappa} = \text{-}7.7$

Contributions to the literature

Differences in cities around the world

Mills and Tan (1980), Lall et al. (2021), Jedwab et al. (2021), Ahlfeldt et al. (2023), Akbar et al. (2023)

$\rightarrow$ framework to link city characteristics to structural parameters that govern a city's size

Back

Contributions to the literature

Differences in cities around the world

Mills and Tan (1980), Lall et al. (2021), Jedwab et al. (2021), Ahlfeldt et al. (2023), Akbar et al. (2023)

$\rightarrow$ framework to link city characteristics to structural parameters that govern a city's size

Role of cities and spatial distribution of economic activity determining aggregate productivity

Au and Henderson (2006), Desmet and Rossi-Hansberg (2013), Bryan and Morten (2019)

$\rightarrow$ focus on the role of urban costs in determining the size of cities and the urban sector

Back

Contributions to the literature

Differences in cities around the world

Mills and Tan (1980), Lall et al. (2021), Jedwab et al. (2021), Ahlfeldt et al. (2023), Akbar et al. (2023)

→ framework to link city characteristics to structural parameters that govern a city's size

Role of cities and spatial distribution of economic activity determining aggregate productivity

Au and Henderson (2006), Desmet and Rossi-Hansberg (2013), Bryan and Morten (2019)

→ focus on the role of urban costs in determining the size of cities and the urban sector

Evaluating the effects of urban transportation infrastructure improvements, esp. in the developing world

Balboni et al. (2020), Kreindler et al. (2023), Kreindler and Miyauchi (2023), Tsivanidis (2023)

→ evaluating the aggregate impact of improving urban infrastructure in many cities

Back

Contributions to the literature

Differences in cities around the world

Mills and Tan (1980), Lall et al. (2021), Jedwab et al. (2021), Ahlfeldt et al. (2023), Akbar et al. (2023)

$\rightarrow$ framework to link city characteristics to structural parameters that govern a city's size

Role of cities and spatial distribution of economic activity determining aggregate productivity

Au and Henderson (2006), Desmet and Rossi-Hansberg (2013), Bryan and Morten (2019)

$\rightarrow$ focus on the role of urban costs in determining the size of cities and the urban sector

Evaluating the effects of urban transportation infrastructure improvements, esp. in the developing world

Balboni et al. (2020), Kreindler et al. (2023), Kreindler and Miyauchi (2023), Tsivanidis (2023)

$\rightarrow$ evaluating the aggregate impact of improving urban infrastructure in many cities

Climate change driving urbanization

Barrios et al. (2006), Henderson et al. (2017), Nawrotzki et al. (2017)

$\rightarrow$ global perspective on climate change and urbanization using a quantitative spatial model

Back

Floorspace development microfoundations

To incorporate marginal land into the city, developers must pay a fixed cost $F_i(x)$ that is rising in x,

$$F_i(x) = \tilde{Z}_i^X (x)^{2/\boldsymbol{\rho_i}}$$

before they can build vertically using,

$$\underbrace{H_i(x, \phi)}_{\text{floorspace}} = \tilde{Z}_i^H C_0^{\frac{\boldsymbol{\gamma_i}}{1+\boldsymbol{\gamma_i}}}$$

i.e., land is a fixed factor with income share $\frac{1}{1+\gamma_i}$.

Isomorphic to a representative developer that can build *up* and *out*, and faces increasing marginal costs to weave land into the urban fabric

Los Angeles: build into the Hollywood Hills; Singapore: land reclamation

Back

Average vs. experienced density

Much of the literature estimates the returns to average density (ζ) (Ahlfeldt and Pietrostefani, 2019)

'Experienced density' may be more appropriate (Duranton and Puga, 2020)

In the model, experienced density can be computed in closed form,

$$2\pi \int_0^{X_i} x \frac{L_i(x)}{L_i} L_i(x) dx = \left(1 - \tau_i \frac{1+\gamma_i}{\beta}\right) X_i^{-\tau_i \frac{1+\gamma_i}{\beta}} \cdot \left(\frac{L_i}{\pi X_i^2}\right)$$

Note this implies,

1. Direct effect of transportation on productivity
2. Larger gap between effects of density vs. city size (L_i)

Back

General equilibrium

Given urban and rural fundamentals, $\{\bar{A}_i, Z_i^H, Z_i^X, \bar{Z}_i^y\}$, urban technology parameters $\{\tau_i, \gamma_i, \rho_i\}$, preference parameters $\{\alpha, \beta, \sigma\}$, production parameters $\{\zeta, \mu\}$ and trade costs $\{\delta_{ij}\}$, an equilibrium is a population distribution across locations $\{L_i\}$, across sites in cities $\{L_i(x)\}$, urban radii $\{X_i\}$, floorspace prices $\{q_i(x)\}$, goods prices $\{p_i\}$, wages $\{w_i\}$, such that,

1. Households, taking wages and prices as given, optimally choose i, x (if choosing a city), alongside floorspace and goods demands;
2. Developers, taking floorspace prices as given optimally choose $H_i(x)$ and X_i;
3. all urban households are housed somewhere, $2\pi \int_0^{X_i} xL_i(x)dx = L_i$;
4. a spatial equilibrium holds within each city, so that utility is equalized across all $x \in (0, X_i]$;
5. The floorspace market clears at each (x, ϕ) in every city;
6. Production firms, taking wages and prices as given, optimally choose labor demand;
7. The goods market clears for the agricultural good and all urban varieties;
8. Developers use their profit to consume the numeraire good, and land rents are rebated back to workers in the agricultural sector. Back

Equilibrium characterization

Proposition An equilibrium in which each city is populated on measurable land exists and is unique if,

$$\frac{\beta}{1+\gamma_i} > \frac{\tau_i}{2}$$

and, ζ is not too large relative to $\min_i \kappa_i$

$$\kappa_i \equiv \frac{1}{1+\rho_i}\frac{\beta}{1+\gamma_i} + \frac{\rho_i}{1+\rho_i}\frac{\tau_i}{2}$$

The first condition restricts the effect of *land* on city-level outcomes.

Two effects of increasing land:

1. lowers floorspace prices everywhere,
2. but increases commuting costs of agents on the periphery.

On net, the price effect must dominate! Back

Equilibrium characterization

Proposition An equilibrium in which each city is populated on measurable land exists and is unique if,

$$\frac{\beta}{1+\gamma_i} > \frac{\tau_i}{2}$$

and, ζ is not too large relative to $\min_i \kappa_i$

$$\kappa_i \equiv \frac{1}{1+\rho_i}\frac{\beta}{1+\gamma_i} + \frac{\rho_i}{1+\rho_i}\frac{\tau_i}{2}$$

The second condition is that congestion $>$ agglomeration. Uniqueness condition Back

Agglomeration vs. congestion: no black holes

Proposition An equilibrium in which each city is populated on measurable land exists and is unique if,

$$\frac{\beta}{1+\gamma_i} > \frac{\tau_i}{2}$$

and, ζ is not too large relative to $\min_i \kappa_i$.

Existence/uniqueness via Allen et al. (2024)

Congestion forces (housing and commuting) must dominate agglomeration forces. Back

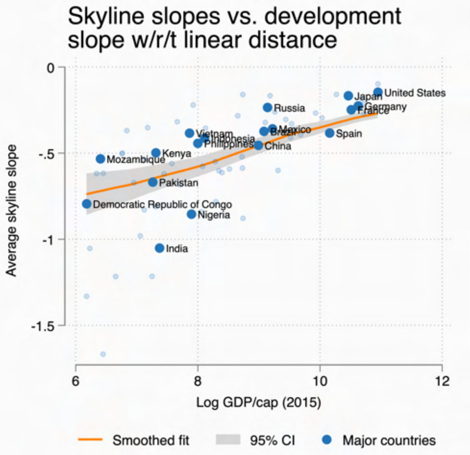
Existence / uniqueness characterization for the calibrated model

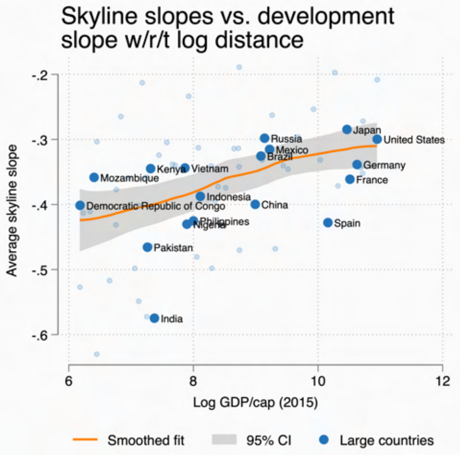
Skyline-slope cross country regression

	log Skyline slope			
	(1)	(2)	(3)	(4)
Log country GDP/cap	-0.039	-0.050	-0.083	-0.071
	(0.019)	(0.020)	(0.024)	(0.024)
Log country population				-0.156
				(0.093)
Log N cities				0.225
				(0.093)
Share urbanized				-0.342
				(0.266)
Observations	10,174	9,539	9,038	9,038
R-squared	0.01	0.01	0.03	0.05
Weighted	✓	✓	✓	✓
No communist		✓	✓	✓
At least 20 cities			✓	✓

Cities' skyline slopes vs. nations country of development. Observations weighted by the inverse number of cities in a country. Standard errors clustered at the country level in parentheses Back

Skyline-slope cross country regression





Average city skyline slopes vs. log GDP/cap Back

What can we learn from city skylines?

Monocentric city model of Alonso/Muth/Mills: circular cities, locations in polar coordinates (x, ϕ)

- x: distance to the central business district

Identical households earn wage w, choose consumption + location; $\beta =$ expenditure share on housing

- Trade off: amenities $A(x, \phi)$ and housing prices $q(x, \phi)$.

Housing developers build housing $H(x, \phi)$, supply elasticity γ.

In equilibrium, no spatial arbitrage: $\underbrace{\bar{A}x^{-\tau}}_{\text{amenities}} \quad \underbrace{u(q(x, \phi), w)}_{\text{indirect consumption utility}} \quad = \quad \underbrace{\bar{u}}_{\text{common utility level}}$

Differentiation w/r/t x + Roy's identity,

$$\underbrace{\frac{d \log h(x, \phi)}{d \log x}}_{\text{skyline slopes}} = -\frac{\boldsymbol{\tau}\ \boldsymbol{\gamma}}{\beta}$$

Skylines are steep if it is easy to build 'up' (γ high) or costly to build 'out' (τ high) Back

Empirical Bayes' estimator

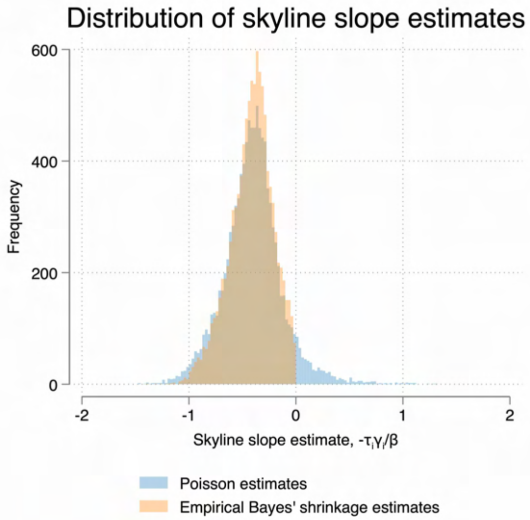
Letting $\hat{\theta}_i^{PPML} = -\widehat{\tau_i \gamma_i / \beta}$, I assume the hierarchical model,

$$\begin{aligned} \hat{\theta}_i^{PPML} \mid \theta_i &\sim N(\theta_i, \sigma_i) \\ \theta_i &\sim \underbrace{N_{(-\infty,0)}(\theta_n, \sigma_n)}_{\text{truncated normal}} \end{aligned} \tag{1}$$

The empirical Bayes' estimates are $\hat{\theta}_i^{EB} = \mathbb{E}[\theta_i \mid \hat{\theta}_i^{PPML}]$, given the model (1).

Key: a truncated normal prior is conjugate with a normal likelihood.

Can estimate parameters of the posterior following Morris (1983) Back



Measuring the land supply elasticity (ρ_i) using the time series on urban growth

Model implies,

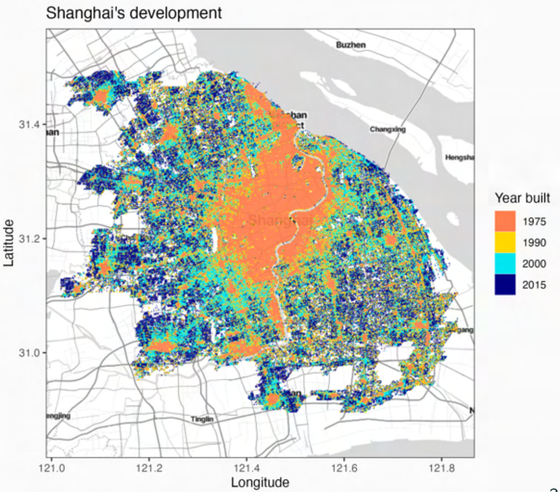
$$\log \pi X_i^2 = \frac{\rho_i}{1+\rho_i} \log w_i L_i + \xi_i$$

where ξ_i contains urban land construction TFP, Z_i^X.

Identification using the time series:

$$\log \text{area}_{it} = \frac{\rho_i}{1+\rho_i} \log w_{it} L_{it} + \underbrace{\xi_i}_{\substack{\text{city} \\ \text{FE}}} + \underbrace{\xi_{rt}}_{\substack{\text{region-year} \\ \text{FE}}} + e_{it}$$

- GDP time series measured with error – instrument with DMSP-OLS nightlights.
- Parameterize $\frac{\rho_i}{1+\rho_i} = G_i'\Omega$.



Measuring the land supply elasticity (ρ_i) using the time series on urban growth

Model implies,

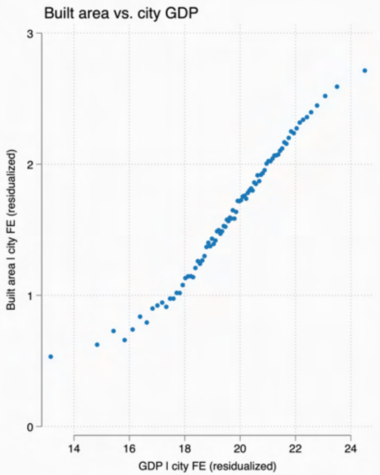
$$\log \pi X_i^2 = \frac{\rho_i}{1+\rho_i} \log w_i L_i + \xi_i$$

where ξ_i contains urban land construction TFP, Z_i^X.

Identification using the time series:

$$\log \text{area}_{it} = \frac{\rho_i}{1+\rho_i} \log w_{it} L_{it} + \underbrace{\xi_i}_{\substack{\text{city}\\ \text{FE}}} + \underbrace{\xi_{rt}}_{\substack{\text{region-year}\\ \text{FE}}} + e_{it}$$

- GDP time series measured with error – instrument with DMSP-OLS nightlights.
- Parameterize $\frac{\rho_i}{1+\rho_i} = G_i' \Omega$.



'Binsreg' conditional on city fixed effects, in logs

Productivity instrument construction

$\bar{Z}_i^y$ solve the system,

$$w_i L_i = \alpha \sum_j \left(\frac{\delta_{ji}(w_i/Z_i^y)}{P_j} \right)^{1-\sigma} w_j L_j, \quad P_j = \left(\sum_j \left(\delta_{ji}(w_j/Z_j^y)\right)^{1-\sigma} \right)^{\frac{1}{1-\sigma}}$$

where $Z_i^y = \bar{Z}_i^y (L_i/\pi X_i^2)^\zeta$. Note,

- w_i, L_i are data,
- δ_{ij}: constructed with intercity road distances & gravity parameters estimated in the U.S. CFS,
- and σ, ζ, α are known ($\sigma = 4$, α matches nat'l accounts, $\zeta = 0.04$).

Therefore city productivity is identified without knowledge of γ_i.

For IV, need $\bar{Z}_i^y \perp Z_i^H \mid$ country FE, geophysical controls.

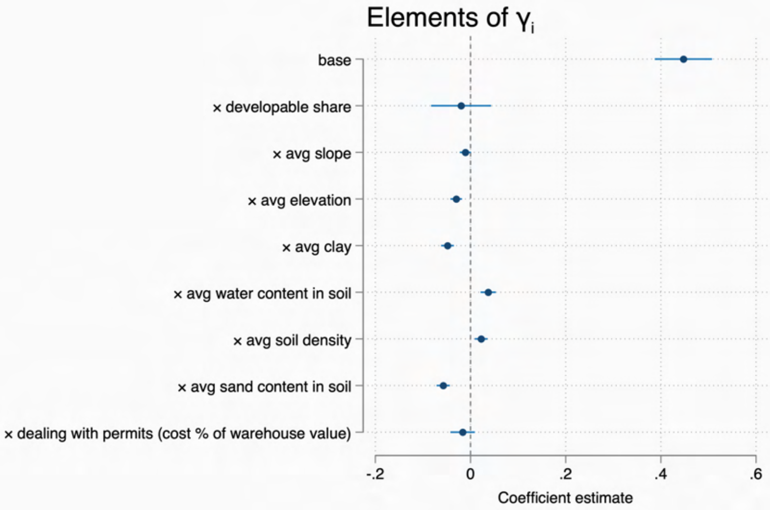
Los Angeles' filmmaking productivity due to its landscape/climate, not seismic activity & deep bedrock

Back

Floorspace supply elasticity estimates – predictors of γ_i

TSLS estimates of γ_i:

geophysical and regulatory predictors of the floorspace supply elasticity Back

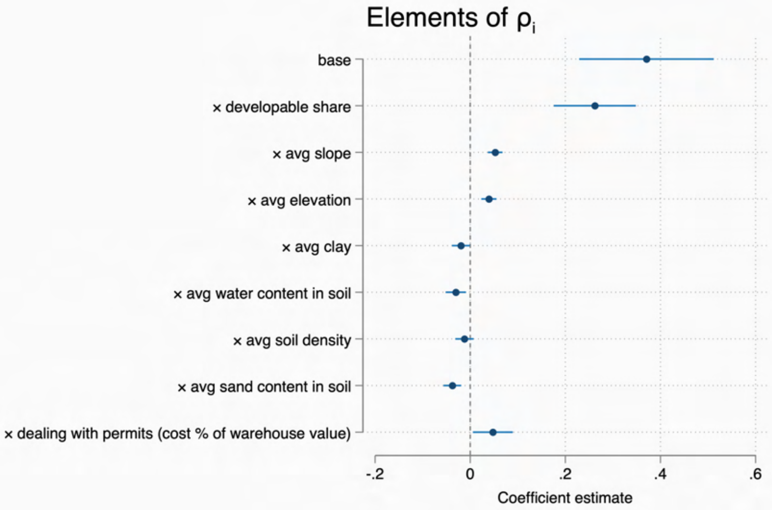


Land supply elasticity estimates – predictors of ρ_i

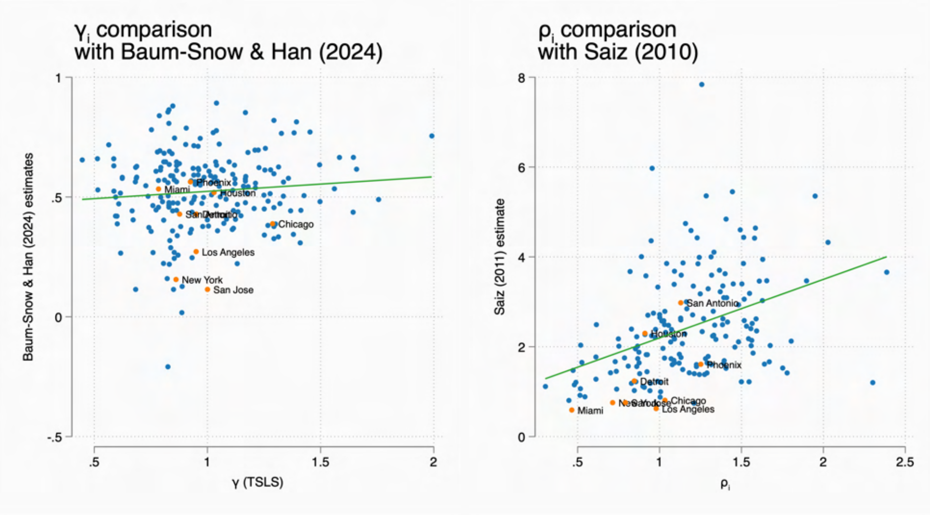
TSLS estimates of ρ_i:

geophysical and regulatory predictors of the land supply elasticity

Back



Comparison of γ_i and ρ_i estimates in the U.S.



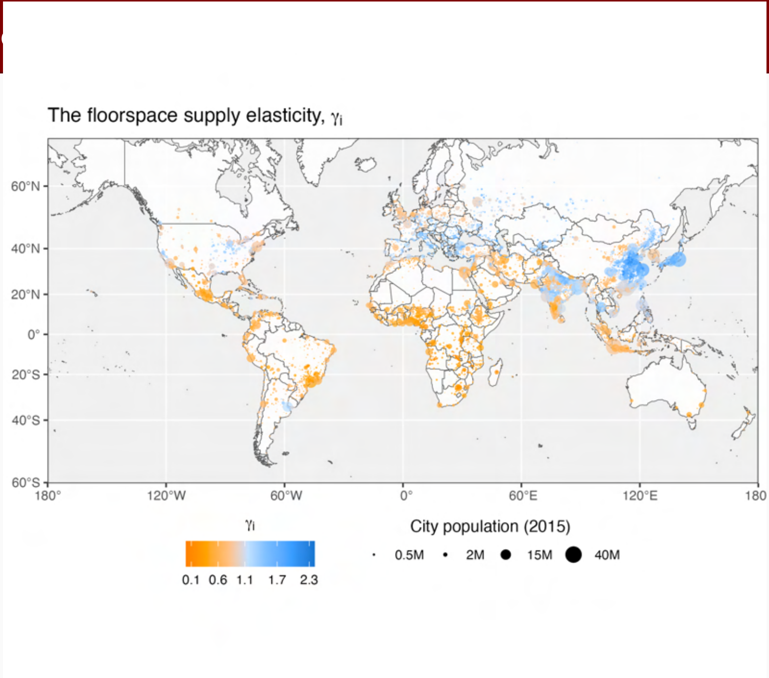
Back

Comparison of τ_i to Akbar et al. (2023, 2024) estimates

	Speed near city center				Speed indices			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log dowtown speed (midnight)	-1.064	-0.374	-1.899	-1.222				
	(0.277)	(0.340)	(0.391)	(0.476)				
log dowtown speed (midday)	0.917	0.239	1.478	0.660				
	(0.238)	(0.307)	(0.278)	(0.417)				
Uncongested speed index					-1.610	-0.219	-3.103	-1.726
					(0.459)	(0.524)	(0.769)	(0.906)
Speed index					1.679	0.185	2.919	1.210
					(0.463)	(0.535)	(0.623)	(0.811)
log pop		-0.090		-0.053		-0.099		-0.067
		(0.038)		(0.044)		(0.036)		(0.043)
log population/km2		0.002		-0.162		0.016		-0.162
		(0.052)		(0.085)		(0.051)		(0.087)
1(primate city)		-0.152		-0.161		-0.155		-0.160
		(0.117)		(0.159)		(0.120)		(0.163)
Observations	856	856	856	856	856	856	856	856
R-squared	0.02	0.04	0.26	0.27	0.02	0.04	0.25	0.27
Country FE			✓	✓			✓	✓

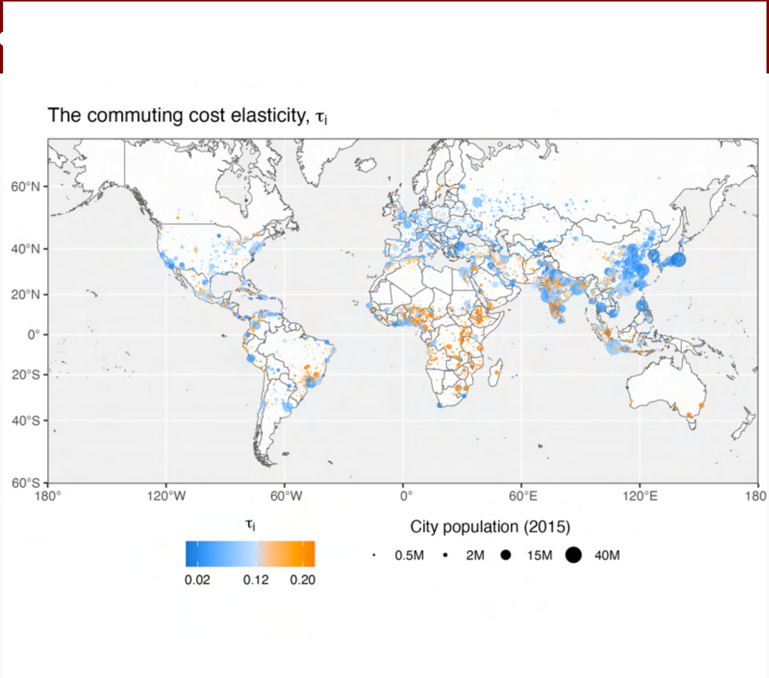
Correlation of log τ_i with city speed variables from Akbar et al. (2023, 2024) Back

Map of γ_i, th



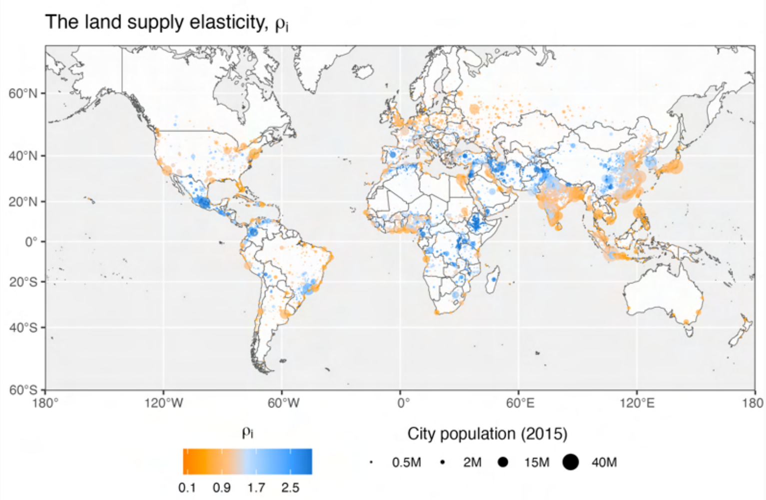
Back

Map of τ_i, th



Back

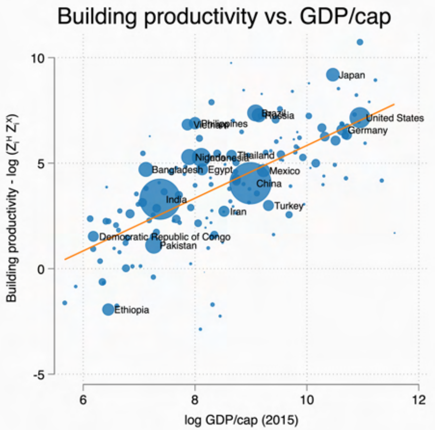
Map of ρ_i, th

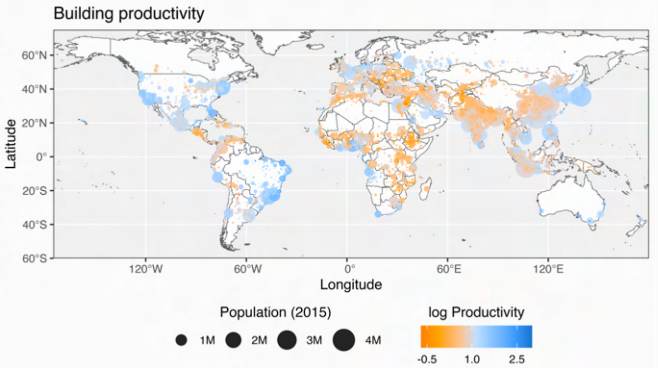


Back

Building productivity – combining Z_i^H and Z_i^X

Welfare relevant parameter: $(Z_i^H)^{\beta}(Z_i^X)^{\frac{\beta}{1+\gamma_i}-}$





Netting out ψ^H, ψ^X Back

Regional breakdown of cities urban cost elasticities (κ_i)

Region	κ_i	τ_i	γ_i	ρ_i
China	0.071	0.084	1.346	1.402
Former Soviet / DPRK	0.071	0.070	1.272	1.206
South Asia	0.097	0.149	1.060	1.317
Latin America and the Caribbean	0.115	0.161	0.620	1.505
North America and Europe	0.082	0.086	1.062	1.136
Southeastern/Eastern Asia and Oceania	0.097	0.107	0.946	0.872
Sub-Saharan Africa	0.149	0.254	0.454	2.087
Western/Central Asia and Northern Africa	0.092	0.123	0.879	1.849

Mean κ_i and its components by region Back

Urban cost elasticities (κ_i) vs. city size

	κ_i		$\log \kappa$	
	(1)	(2)	(3)	(4)
log GDP/cap (country)	-0.013		-0.081	
	(0.002)		(0.013)	
log GDP/cap (city)		-0.006		-0.036
		(0.001)		(0.003)
log population (city)		-0.006		-0.036
		(0.000)		(0.003)
Observations	127	9,358	127	9,358
R-squared	0.25	0.39	0.25	0.39
R-squared (within)		0.04		0.03
Country FE		✓		✓

Regressions of κ_i against city size variables Back

Calibrated parameters

Parameter	Value	Description	Source
ζ	0.04	Elasticity of urban productivity with respect to density	Combes et al. (2010) and Ahlfeldt and Pietrostefani (2019)
σ	4	intercity trade elasticity	Bajzik et al. (2020)
β	0.25	share of income spent on housing	Average across countries where observed (World Bank 2017 ICP)
$1 - \alpha_n - \beta$	–	Share of income spent on agricultural goods	Calibrated to match World Bank Development Indicators in 2015 on the share of agricultural value-added in national income
μ	0.7	share of land in agricultural goods production	Chari et al. (2021)
ε	1.17	migration elasticity	Suárez Serrato and Zidar (2016) and Sahai and Bailey (2022)

Back

Gravity in the U.S. CFS

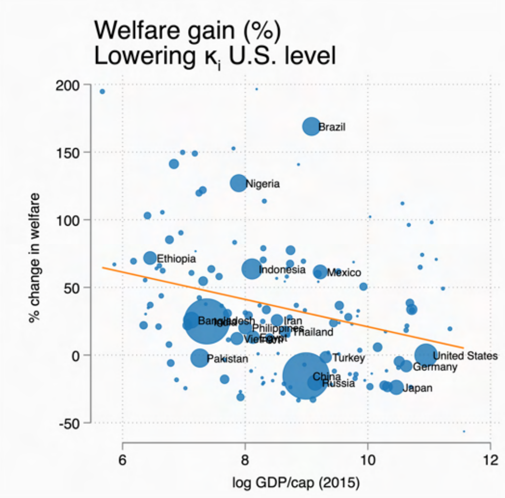
Intercity road shipment values + distance from U.S. Commodity Flows Survey.

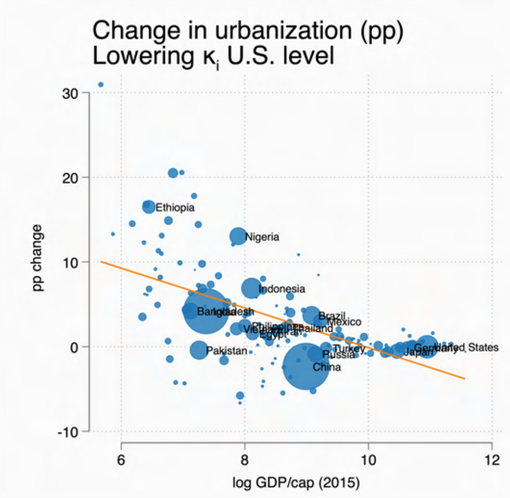
Back

	(1) Shipment value
Log dist	-0.923
	(0.022)
N	4,817

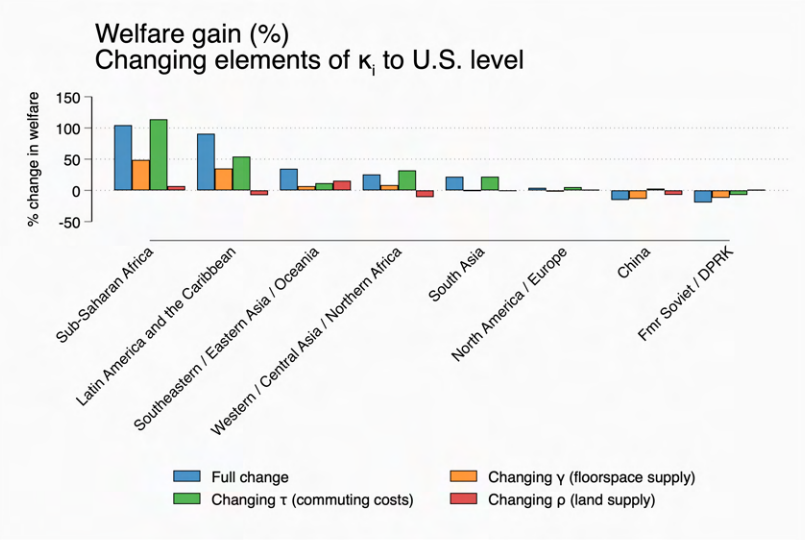
Gravity regression in the CFS

Lowering the urban cost elasticity (κ_i) to the U.S. level – overall welfare effect





Lowering the urban cost elasticity (κ_i) to the U.S. level – elements of κ_i



Back

Decomposing κ_i

	τ_i	γ_i	ρ_i
Coefficient	0.321	-0.034	-0.003
	(0.003)	(0.001)	(0.000)
Partial R-squared	0.473	0.242	0.022

Table 1: Coefficients and partial R^2 statistics from a regression of κ_i against its components

Back

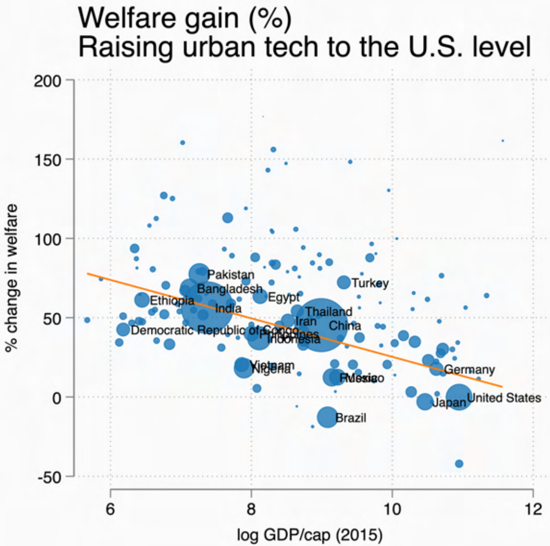
Raising building technology $(Z_i^H)^\beta (Z_i^X)^{\frac{\beta}{1+\gamma_i} - \frac{\tau_i}{2}}$ to the U.S. level

Average (pop-weighted) welfare increases:

Low-income nations: (GDP/cap $<$ \$4,000 USD)	56%
Middle-income nations:	41%
Low-income nations: (GDP/cap $>$ \$20,000 USD)	14%

Global Gini for PPP-adjusted GDP/cap $\downarrow$ 11%

Back



Raising building technology $(Z_i^H)^\beta (Z_i^X)^{\frac{\beta}{1+\gamma_i} - \frac{\tau_i}{2}}$ to the U.S. level

Welfare in nation n,

$$\mathcal{W}_n = \mathbb{E}[v_i \epsilon_i \mid v_i \epsilon_i \geq \max_j v_j \epsilon_j]$$

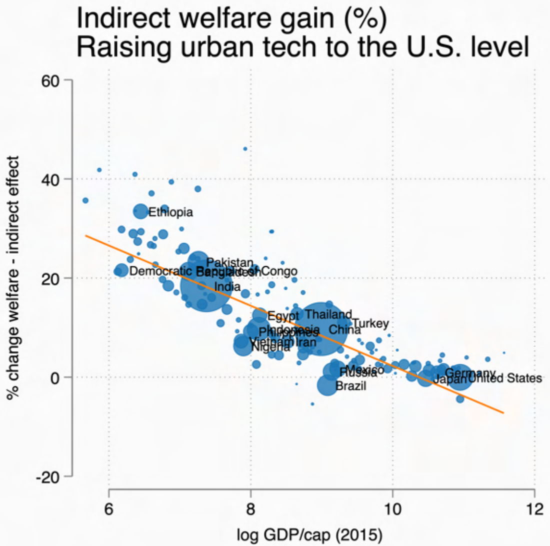
$$\propto \left(\sum_i \left(\tilde{A}_i \frac{w_i}{P_i^\alpha} (w_i L_i)^{-\kappa_i} \right)^\varepsilon \right)^{1/\varepsilon}$$

Can decompose the effect,

$$\frac{d\mathcal{W}_n}{\mathcal{W}_n} = \text{direct effect} + \text{indirect effect}$$

$$\text{direct} = \sum_i \left(\frac{L_i}{L_n} \right) \frac{d\tilde{A}_i}{\tilde{A}_i}$$

$$\text{indirect} = \sum_i \left(\frac{L_i}{L_n} \right) \left(\frac{d(w_i/P_i^\alpha)}{(w_i/P_i^\alpha)} - \kappa_i \frac{d(w_i L_i)}{w_i L_i} \right)$$



Netting out ψ^H, ψ^X

Only physical quantity of floorspace observed, H_i, need to adjust for quality differences across space.

Model:

$$\psi_n^H q_n \sum_i H_i = \beta \sum_i w_i L_i, \quad \psi_n^X q_n \sum_i \pi X_i^2 = \beta \sum_i \frac{w_i L_i}{1+\gamma_i}$$

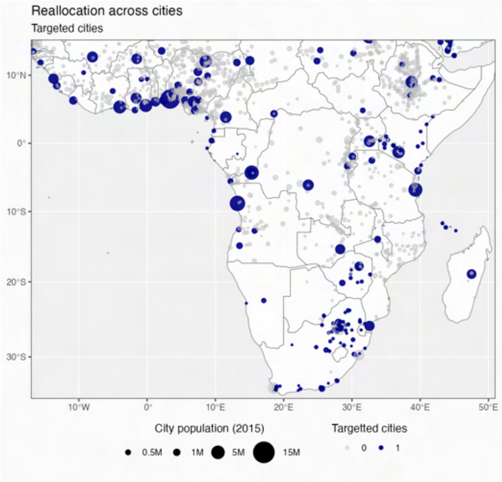
q_n: average floorspace price.

Liotta et al. (2022, RSUE) – floorspace prices per m^2 in some cities in 49 countries in local currency.

PPP adjust to USD. For other nations: Random Forest to predict q_n using country-level covariates (size, income, PPP deflator).

Back

Road paving: targeted cities in SSA



Back