Shift-Share IV

Mixtape Track

Roadmap

- Motivation
- Intuition
  - Market Access Effects
  - Medicaid Eligibility Effects
- Formal Framework
- Applications
  - Market Access Effects
  - Medicaid Eligibility Effects
- Concluding Thoughts

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How can we just leverage the exogenous shocks to such z_i?

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   - → Conventional solutions (e.g. directly instrumenting with shocks or controlling for all features of exposure) are often infeasible
3. Recentering solution also can have attractive efficiency properties
   - → Leverages non-random exposure to best predict shock effects

(Some) Other Settings where these Points are Relevant

Linear shift-share IV (Autor et al. 2013, Borusyak et al. 2022)

Nonlinear shift-share IV (Boustan et al. 2013, Berman et al. 2015, Chodorow-Reich and Wieland 2020, Derenoncourt 2021)

IV based on centralized school assignment mechanisms (Abdulkadiroğlu et al. 2017, 2019, Angrist et al. 2020)

Model-implied optimal IV (Adão-Arkolakis-Esposito 2021)

Weather instruments (Gomez et al. 2007, Madestam et al. 2013)

“Free space” instruments for mass media access (Olken 2009, Yanagizawa-Drott 2014)

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Theory suggests transportation upgrades affect local outcomes (e.g. land value) of regions i by increasing their market access (MA):

$$\Delta \log V_i = \beta \Delta \log MA_i + \varepsilon_i,$$

$$\text{where } MA_{it} = \sum_j \tau(g_t, loc_i, loc_j)^{-1} pop_j,$$

for road network g_t in periods $t = 1, 2$, region locations loc_j (co-determining travel cost τ), and regional population pop_j

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No. Randomizing roads $\nRightarrow$ randomizing MA due to them!

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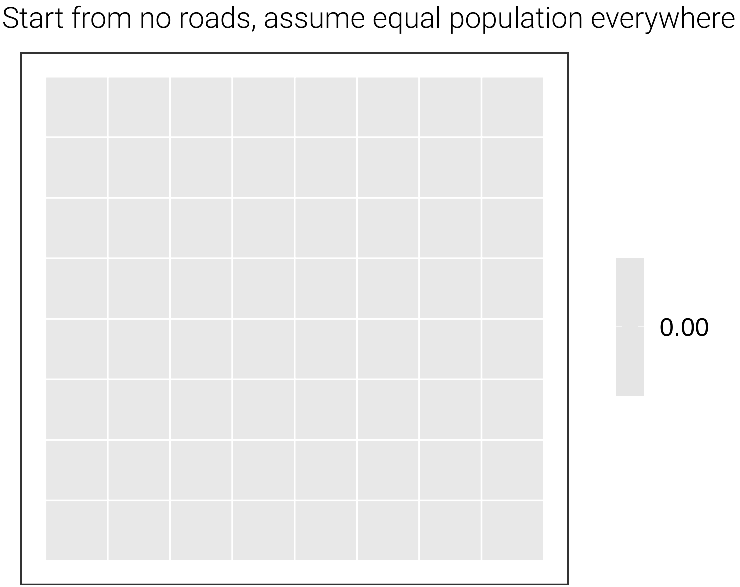

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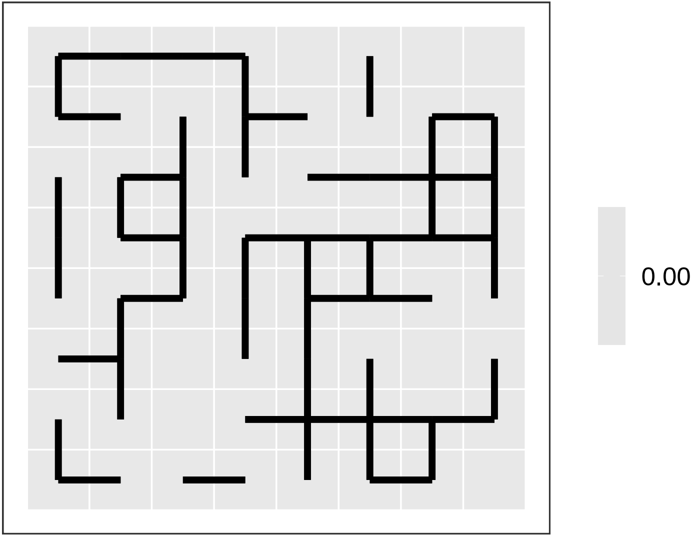

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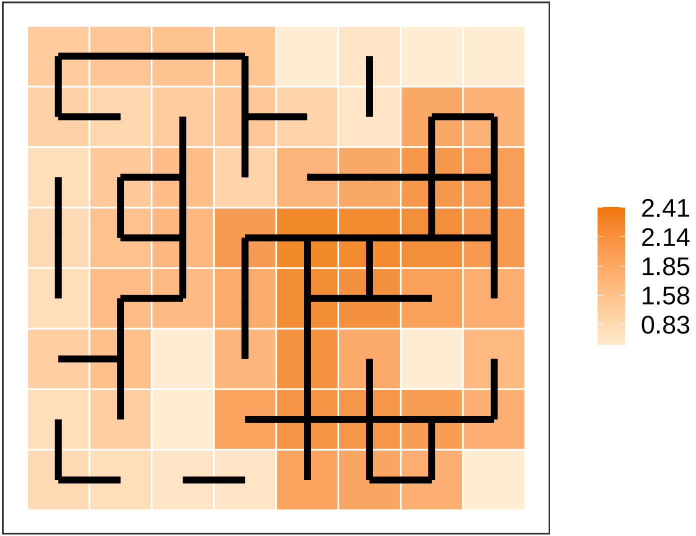

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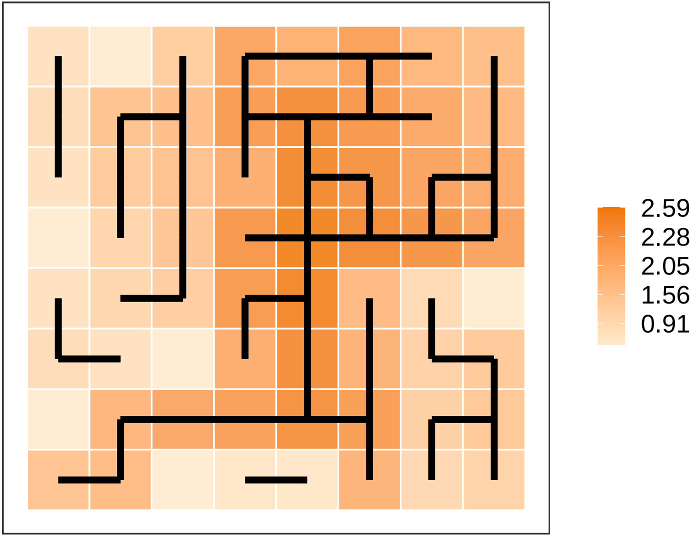

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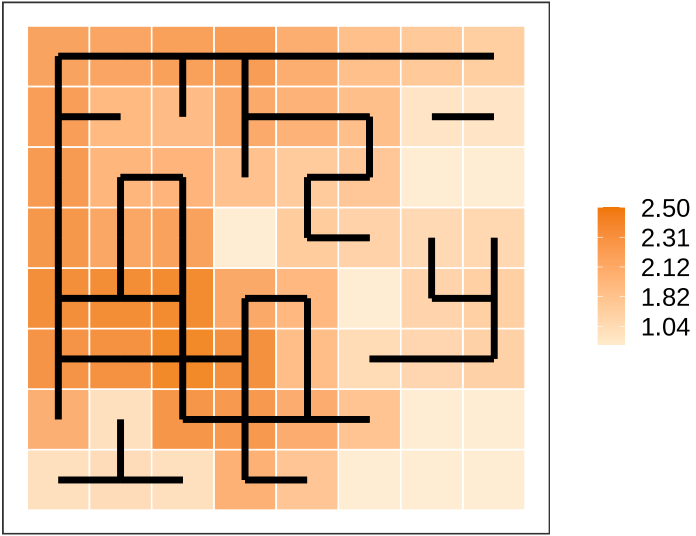

Expected Market Access Growth μ_i

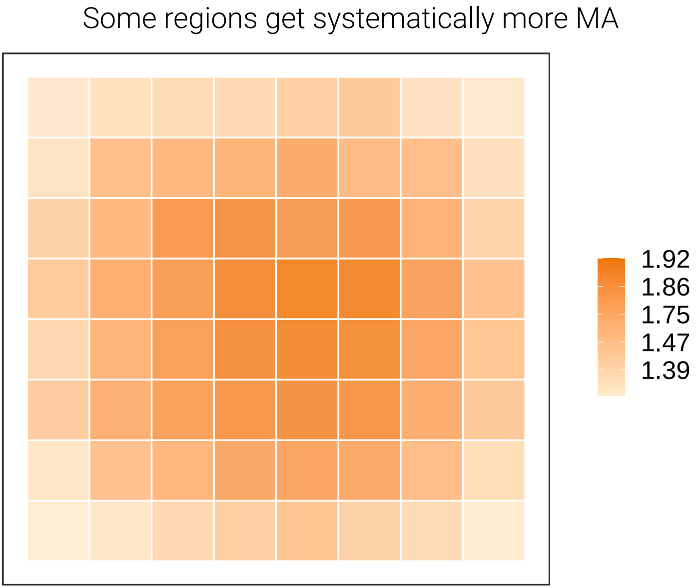

Illustration: High-Speed Rail in China

149 lines were built or planned (as of April 2019)

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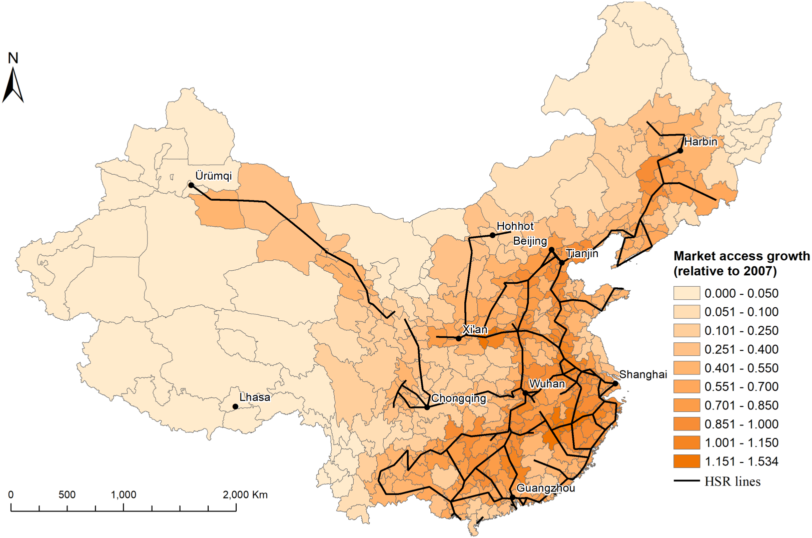
The 83 lines actually built by 2016. Suppose timing is random



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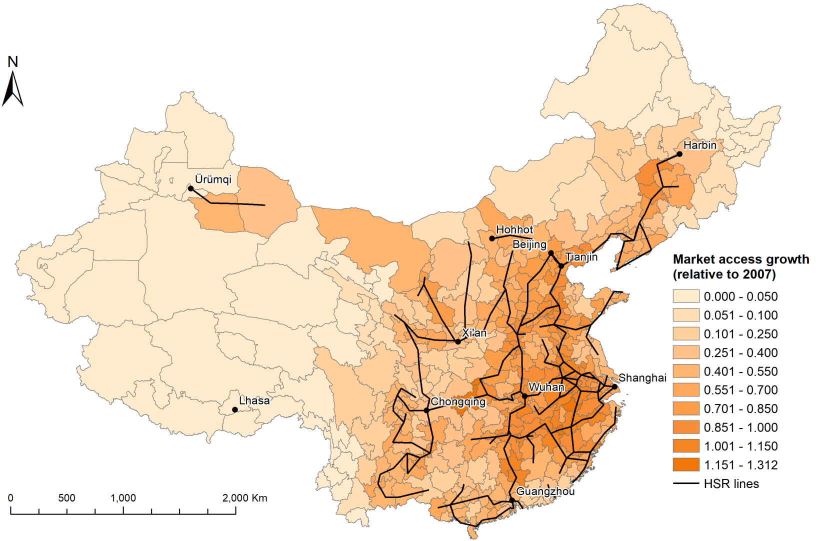
A counterfactual draw of 83 lines by 2016



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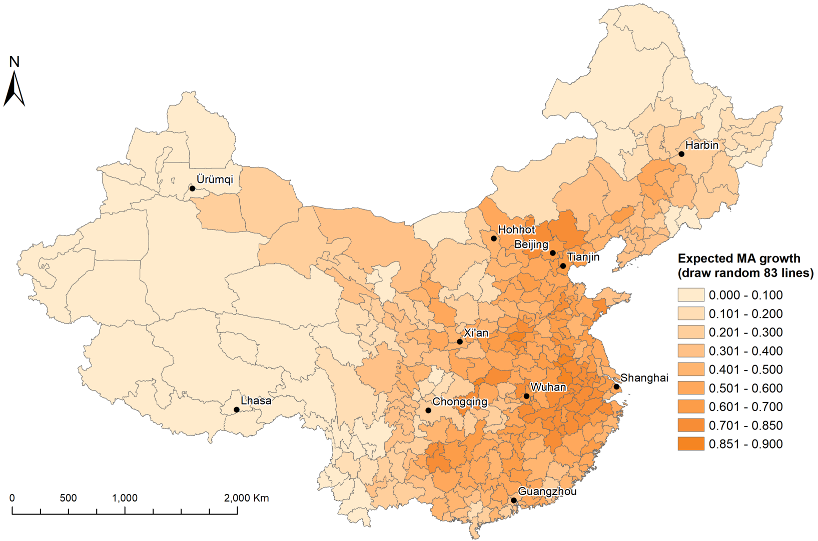
Expected MA growth, μ_i



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Recentered MA is a valid instrument for realized MA growth

- Compares MA from actual and counterfactual shocks
- As it turns out, we can also control for expected MA growth

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- Controlling for $\sum_n s_{in} q_n$ is enough (sound familiar?)

Example 2: Effects of Program Eligibility

Consider the effects of individual eligilibity x_i for Medicaid:

$$y_i = \beta x_i + \varepsilon_i$$

where x_i is determined by i's state policy g_{state_i} and demographics

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Standard "simulated instruments" solution (Currie and Gruber (1996)): use state-level variation (avgerage policy generosity across a "simulated" group of individuals) as a single IV for x_i

- This works, but is likely inefficient: the policy shocks likely have heterogeneous effects across individuals w/different demos

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- Yields efficiency gain by better first-stage prediction, e.g. by removing i who are always or never eligible

Roadmap

General Setup

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We have a candidate instrument $z_i = f_i(g, w)$, where g is a vector of shocks; w collects predetermined variables; $f_i(\cdot)$ are known mappings

- Applies to any z_i which can be constructed from observed data
- Nests reduced-form regressions: $x_i = z_i$
- Allows $g = (g_1, \dots, g_K)$ to vary at a different level than i

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Assumptions:

1. Shocks are exogenous: $g \perp \varepsilon \mid w$
2. Conditional distribution $G(g \mid w)$ is known (e.g. via randomization protocol or uniform across permutations of g)

Main Results

The expected instrument, $\mu_i = E[f_i(g, w) \mid w] \equiv \int f_i(g, w) dG(g \mid w)$, is the sole confounder generating OVB:

$$E\left[\frac{1}{N}\sum_i z_i \varepsilon_i\right] = E\left[\frac{1}{N}\sum_i \mu_i \varepsilon_i\right] \neq 0, \text{ in general}$$

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Regressions which control for μ_i also identify β (implicitly recenter, by the FWL theorem)

Extensions

Consistency: follows when $\tilde{z}_i$ is weakly mutually dependent across i

Robustness to heterogeneous treatment effects: $\tilde{z}_i$ identifies a convex avg. of β_i under appropriate first-stage monotonicity

Randomization inference provides exact confidence intervals for β (under constant effects) and falsification tests

BH also characterize the **asy. efficient** recentered IV among all $f_i(\cdot)$

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Formal Framework

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Concluding Thoughts

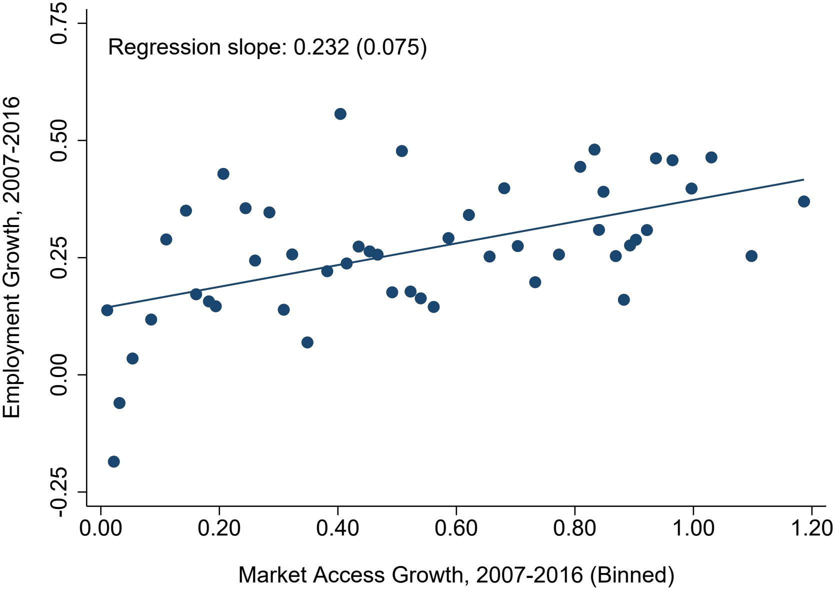
App. 1: Market Access from Chinese High-Speed Rail

BH first show how instrument recentering can address OVB when estimating the effects of market access growth

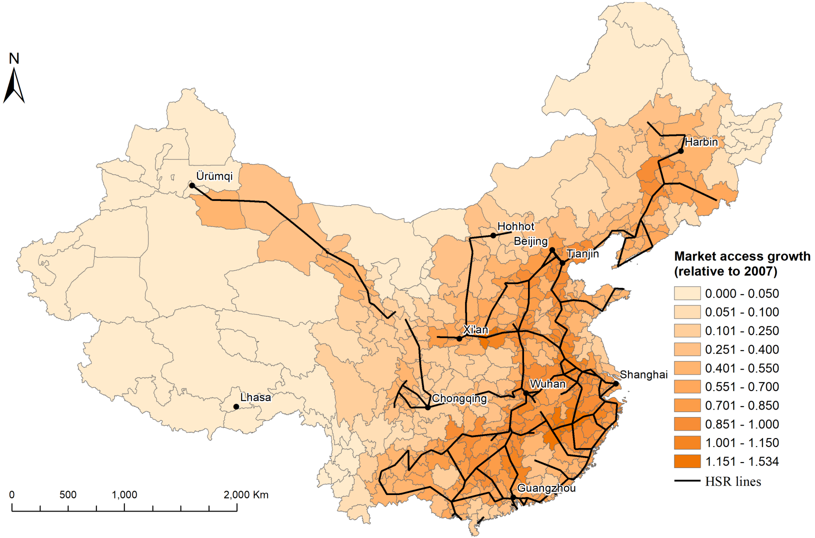
Setting: Chinese HSR; 83 lines built 2008–2016, 66 yet unbuilt

- Market access: $MA_{it} = \sum_k \exp\left(-0.02\tau_{ikt}\right) p_{k,2000}$, where τ_{ikt} is HSR-affected travel time between prefecture capitals (Zheng and Kahn, 2013) and $p_{i,2000}$ is prefecture i's population in 2000
- Relate to employment growth in 274 prefectures, 2007-2016

Simple OLS Regressions Suggest a Large MA Effect



High vs. Low MA Growth is Not a Convincing Contrast!



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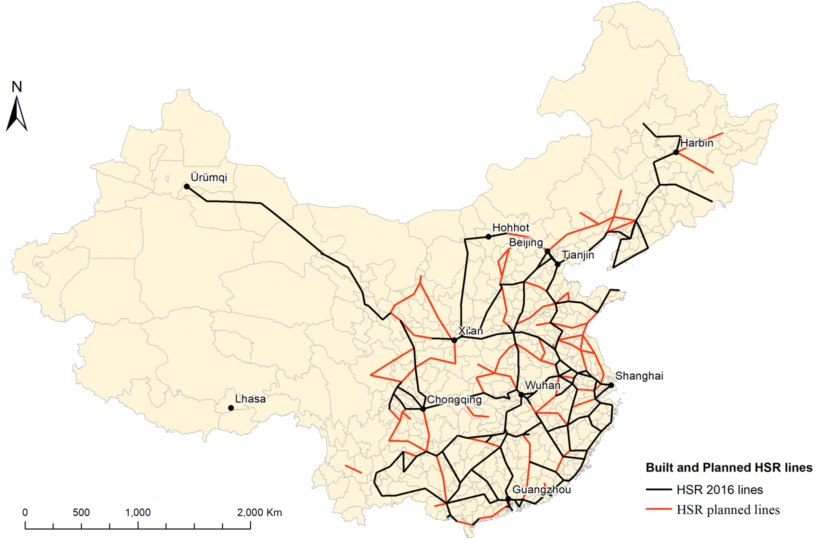
Find valid contrasts for *one* source of variation—a natural experiment

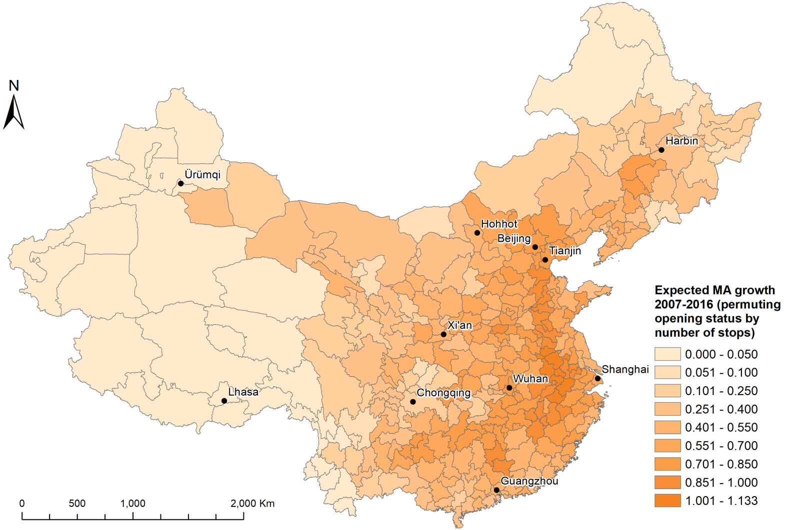
- Bartelme (2018): shocks affecting market size
- Donaldson (2018): built vs unbuilt lines
- BH application: assume random timing of observably similar lines

Built and Planned HSR Lines

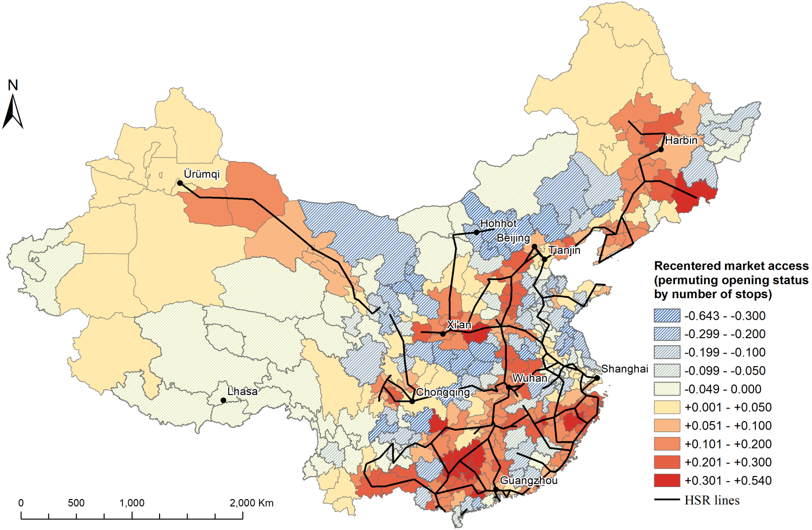
BH reshuffle built & planned lines connecting the same # of regions



Expected Market Access Growth (2007–2016), μ_i



Recentered Market Access Growth (2007–2016), $\tilde{z}_i$

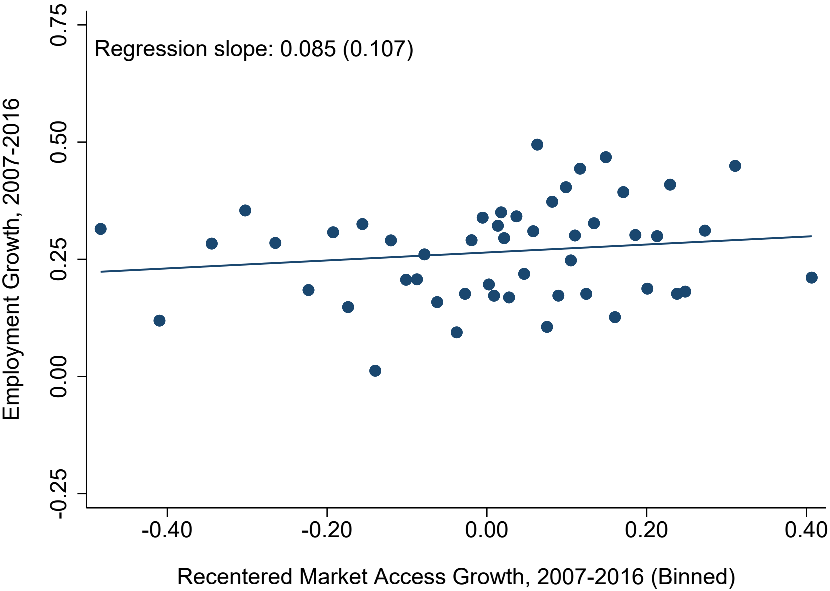


Market Access Balance Regressions

	Unadjusted	Recentered		
	(1)	(2)	(3)	(4)
Distance to Beijing	−0.292	0.069		0.089
	(0.063)	(0.040)		(0.045)
Latitude/100	−3.323	−0.325		−0.156
	(0.648)	(0.277)		(0.320)
Longitude/100	1.329	0.473		0.425
	(0.460)	(0.239)		(0.242)
Expected Market Access Growth			0.027	0.056
			(0.056)	(0.066)
Constant	0.536	0.014	0.014	0.014
	(0.030)	(0.018)	(0.020)	(0.018)
Joint RI p-value		0.489	0.807	0.536
R^2	0.823	0.079	0.007	0.082
Prefectures	274	274	274	274

Regressions of unadjusted and recentered market access growth on geographic features. Spatial-clustered standard errors in parentheses.

Recentered MA Doesn't Predict Employment Growth!



Adjusted Estimates of Market Access Effects

	Unadjusted OLS (1)	Recentered IV (2)	Controlled OLS (3)
Panel A. No Controls			
Market Access Growth	0.232	0.081	0.069
	(0.075)	(0.098)	(0.094)
		[-0.315, 0.328]	[-0.209, 0.331]
Expected Market Access Growth			0.318
			(0.095)
Panel B. With Geography Controls			
Market Access Growth	0.132	0.055	0.045
	(0.064)	(0.089)	(0.092)
		[-0.144, 0.278]	[-0.154, 0.281]
Expected Market Access Growth			0.213
			(0.073)
Recentered	No	Yes	Yes
Prefectures	274	274	274

Regressions of log employment growth on log market access growth in 2007–2016. Spatial-clustered standard errors in parentheses; permutation-based 95% CI in brackets

App. 2: Efficient Estimation of Medicaid Effects

Setting: U.S. Medicaid, partially expanded in 2014 under the ACA

- 19 of 43 states with low Medicaid coverage expanded to 138% FPL
- View expansion decisions as random across states with same-party governors, but not household demographics or pre-2014 policy
- Outcomes: Medicaid takeup and private insurance crowdout

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Via non-random variation, recentered IV has ≈ 3 times smaller SEs

Estimates with Simulated vs. Recentered IV

	Has Medicaid		Has Private Insurance		Has Employer-Sponsored Insurance	
	Simulated IV	Recentered IV	Simulated IV	Recentered IV	Simulated IV	Recentered IV
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Eligibility Effects						
Eligibility	0.132	0.072	−0.048	−0.023	0.009	−0.009
	(0.028)	(0.010)	(0.023)	(0.007)	(0.014)	(0.005)
	[0.080,0.216]	[0.051,0.093]	[-0.110,0.009]	[-0.040,-0.007]	[-0.034,0.052]	[-0.021,0.004]
Panel B. Enrollment Effects						
Has Medicaid			−0.361	−0.321	0.068	−0.125
			(0.165)	(0.092)	(0.111)	(0.061)
			[-0.813,0.082]	[-0.566,-0.108]	[-0.232,0.421]	[-0.263,0.070]
P-value: SIV=RIV			0.719		0.104	
Exposed Sample	N	Y	N	Y	N	Y
States	43	43	43	43	43	43
Individuals	2,397,313	421,042	2,397,313	421,042	2,397,313	421,042

1% ACS sample of non-disabled adults in 2013–14, diff-in-diff IV regressions using one of the two instruments. Controls include state and year fixed effects and an indicator for Republican governor interacted with year. State-clustered standard errors in parentheses; wild score bootstrap 95% CI in brackets

Roadmap

- Motivation
- Intuition
  - Market Access Effects
  - Medicaid Eligibility Effects
- Formal Framework
- Applications
  - Market Access Effects
  - Medicaid Eligibility Effects
- Concluding Thoughts

Conclusions

In both linear SSIV and more elaborate settings, the most important thing is to decide *ex ante* what identifying variation you want to use

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Much more work to be done on the various econometrics here!

Keep Calm and SSIV On!

Good luck on your future adventures with SSIV!

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