Estimating the Impacts of Spatially-Biased Policies

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Plan for this talk

- Overview of empirical approaches for studying spatially biased policies
- Empirical approaches in a broad sense
  - Identifying internally valid causal effects
  - Matching evidence with appropriate questions
  - Role of economic models/theory
- Many policies disproportionately affect particular locations
  - Redistribution / anti-poverty policies
  - Policies for correcting or harnessing externalities
  - Public goods provision
  - Insurance / recovery

Broad groupings

- Sufficient statistics for welfare analysis
  - Albouy (2009)
  - Busso et al (2013)
- IO-style demand estimation (BLP)
  - Bayer, Ferreira, and McMillan (2009)
  - Galiani, Murphy, Pantano (2015)
  - Davis, Gregory, Hartley, Tan (2021)
- Hedonic modeling
  - Diamond and McQuade (2019)
- Causal inference, targeted to estimate structural model
  - Soltas (2024)
  - Fu and Gregory (2019)
- Quantitative Spatial Equilibrium Models
  - Rossi-Hansberg, Esteban, Pierre-Daniel Sarte, and Felipe Schwartzman (2023)

Source of deadweight losses (DWLs)

- Workers and firms are mobile.
- Workers leaving their preferred location to avoid taxes or gain a subsidy $\longrightarrow$ DWL
- Albouy (2009) quantifies DWL due to fed. income tax's distortion to location choices
- When a policy distorts location incentives to achieve a specific objective, optimal policy balances the size of any welfare gain from achieving that objective against the deadweight loss associated with distortion to location choices

Albouy (2009)

Albouy, David. (2009). "The Unequal Geographic Burden of Federal Taxation." Journal of Political Economy, 117(4), 635–667.

Albouy (2009)

- **Motivation:**
  – Federal income taxes computed based on nominal income, ignore differences in wages and cost of living across cities

- **Research question**: Do U.S. federal taxes fall unevenly across locations, and does that distort where people live and work?

- **Key contribution**
  – Extends the Rosen–Roback spatial-equilibrium model to embed federal taxation
  – Derives expressions for DWL
  – Calibrates model to 241 metros and 49 non-metro areas

Conceptual framework

- Key ingredients: fully-mobile workers, homogeneous preferences
- Three city attributes drive real-wage differentials
  1. Quality of life Q
  2. Traded-sector productivity A_X
  3. Home-sector productivity A_Y

$$
\begin{aligned}
&\text{(Worker utility)} && U = Q \times U(\overbrace{x}^{\text{traded}}, \overbrace{y}^{\text{home}}) && (1)\\
&\text{(Traded goods)} && X = A_X \times F(L_X, N_X, K_X) && (2)\\
&\text{(Home goods)} && Y = A_Y \times G(\underbrace{L_Y}_{\text{land}}, \underbrace{N_Y}_{\text{labor}}, \underbrace{K_Y}_{\text{capital}}) && (3)
\end{aligned}
$$

- Mechanism
  - Federal taxes tied to *nominal* wages act like a location-specific head tax.
  - Higher-wage cities face an implicit surtax; lower-wage areas receive a subsidy.

Spatial equilibrium conditions (levels)

$$\text{(worker mobility)} \qquad u_j(X, Y, Q) = \bar{u} \longrightarrow \qquad \frac{[e(p_j, \bar{u}, \overbrace{1}^{\mathsf{Q}}) + \tau(m_j)]}{Q_j} = m_j \tag{1}$$

$$\text{(capital mobility)} \qquad i_j = \bar{i} \longrightarrow \qquad \frac{c_X(r_j, w_j, \bar{\imath})}{A_X^j} = 1 \tag{2}$$

$$\frac{c_Y(r_j, w_j, \bar{\imath})}{A_Y^j} = p_j \tag{3}$$

Notation

- p_j = local home goods price
- m_j = nominal income of a representative worker in j; $\tau(m_j)$ = federal tax
- c_X, c_Y : cost functions (1 unit) in the traded-good and home-good sectors
- r_j, w_j : land rent and wage in city j; $\bar{\imath}$ is the nationwide cost of capital

Log-linearized equilibrium system

Notation: $\hat{z}^j \equiv \ln z^j - \ln \bar{z}$ is the % deviation of city j from the national geometric mean.

(4a) Worker indifference: $$s_w \, \hat{w}^j \quad -s_y \, \hat{p}^j \quad = \tau_0 \, s_w \, \hat{w}^j - \hat{Q}^j \tag{4}$$

(4b) Trade-sector zero profit: $$\phi_L \, \hat{r}^j \quad +\phi_N \, \hat{w}^j \quad = \hat{A}_X^j \tag{5}$$

(4c) Home-sector zero profit: $$\theta_L \, \hat{r}^j \quad +\theta_N \, \hat{w}^j \quad -\hat{p}^j \quad = \hat{A}_Y^j \tag{6}$$

Together, (4a)–(4c) let us back out the unobservable city amenities $(\hat{Q}, \hat{A}_X, \hat{A}_Y)$ from observed prices (wages $\hat{w}$, land rents $\hat{r}$, and housing prices $\hat{p}$).

Consequence of Federal Taxation

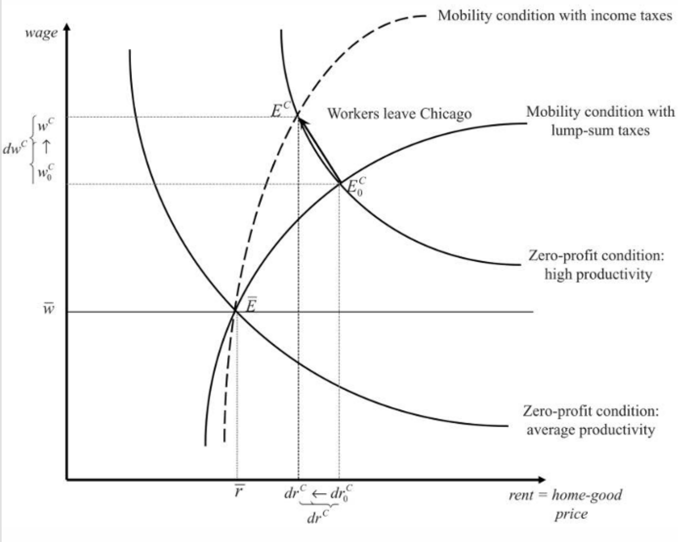
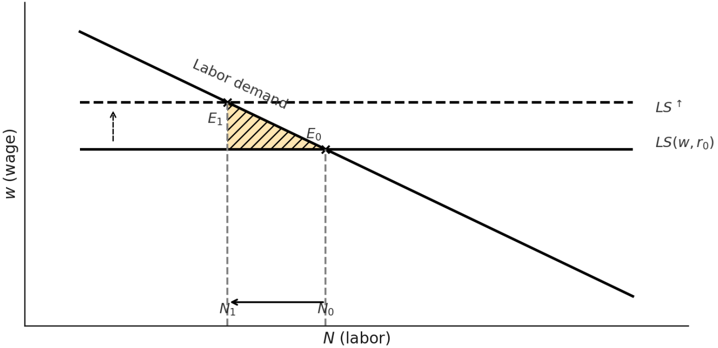


FIG. 1.—Effect of federal taxes on a high trade-productivity city. In a simplified model

Consequence of Nominal-Income Taxation, High-Productivity City



Impact of federal taxation for high-productivity city.

Empirical ingredients & calibration

- Wages: Hourly earnings of full-time workers aged 25–55, controlling for X_i's.
- Housing prices: Rents and owner-occ. values $\longrightarrow$ local price index.
- Federal parameters
  - Marginal tax rate $\tau_0 = 0.33$ (income + payroll).
  - Average housing/state-tax deduction $d \approx 0.26$.
- Cost shares (benchmark)
  - Land 10%, capital 15%, labor 75% of national income.
- Local-employment elasticity to a net-of-tax shift: -6.0 (Bartik meta-elasticities).

Quantitative results (benchmark)

- Average differential: Worker in a high-wage metro pays **+2.4 %** more in federal tax; counterpart in low-wage non-metro receives **–2.4 %**.
- Selected outcomes
  - New York & San Francisco: federal burden ≈ 27 % above rural South.
  - Long-run emp. *–13%* in high-wage areas; land prices *–21%*; housing prices *–5%*.
  - Deadweight loss ≈ 0.23% of income ($\sim \$28$ bn/yr in 2008 $).
- Role of deductions: Removing them raises dispersion by $\sim$ 35 % and nearly doubles welfare loss.
- Federal spending offsets tilt *against* high-tax metros; they do not neutralize the burden.

Where does the $28 bn DWL come from?

- Harberger triangle for migration distortions:

$$\frac{\text{DWL}}{\bar{m}N_{\text{TOT}}} = \frac{1}{2}\,\mathrm{Var}\Big(\frac{d\tau_j}{m}\Big)\,\varepsilon$$

- With linear taxes $\dfrac{d\tau_j}{m} = \tau_0\, s_w\, \hat{w}_j$, so the only empirical input is the cross-city wage dispersion already estimated for eqs. (4a–4c).

- Calibration

$$\tau_0 = 0.33,\ s_w = 0.75,\ \varepsilon = -6.0,\ \mathrm{Var}(\hat{w}_j) = 0.017 \implies \text{DWL} = 0.0023\,\bar{m}N_{\text{TOT}}.$$

$\Rightarrow$ **0.23% of U.S. labor income $28 bn (2008 $)**

Busso, Gregory, and Kline (2013)

Busso, Matias, Jesse Gregory, and Patrick Kline. (2013). "Assessing the Incidence and Efficiency of a Prominent Place-Based Policy." American Economic Review, 103(2), 897–947.

Federal Urban Empowerment Zones (round I)

- Large, federally funded place-based program (Round I: six urban EZ's, 1994).
  - **Employment Tax Credits:** 20% of first $15,000 for zone residents
  - **Social Services Block Grants**
- Research question: *Who benefits and at what efficiency cost?*
- Classic Rosen–Roback model predicts full capitalization into land rents if workers and firms are perfectly mobile.
- This paper:
  - Tests those predictions using "sufficient statistic" approach, derived from general equilibrium sorting model.
  - Requires estimating EZ treatment effects on local employment, wages, rents

Why policymakers use “EZ” style place–based policies

- **Antipoverty**: Spur job creation and investment, boost wages in very poor areas
  - Evidence mixed on emp. effects of state-level policies (Neumark and Simpson, 2015)
- Other rationales:
  - **Big push:** Thin local labor markets and missing agglomeration thresholds.
  - **Spatial mismatch** between workers and jobs.
  - Little empirical support
- **Alternative to income-conditioned, person-based transfers** that generate a work-disincentive (and thus excess burdens)

Model

- **Locations** $j \in \{N_0, N_1\}$ (*outside* neighborhoods vs. *inside* the EZ neighborhoods).
- **Sectors** $s \in \{1, 2\}$ $s = 1 =$ covered firms, $s = 2 =$ uncovered.
- **Workers** choose residence j, workplace k, sector s with idiosyncratic taste ε_{ijks}:

$$u_{ijks} = w_{jks} - r_j - \kappa_{jk} + A_j + \varepsilon_{ijks}.$$

- **Firms** compete in perfectly elastic national goods market (labor demand horizontal in $(w - \tau)$).
- **Landlords** set rent r_j; fixed land endowment, upward-sloping $S_H(r)$.
- **Government** offers wage credit τ per eligible worker and block-grant G to EZ.

Linking Primitives to Equilibrium Prices

1. **Labor-market equilibrium**

$$\underbrace{w_{jks}}_{\text{wage}} = \frac{B_k R(\rho)}{1 - \tau\,\delta_{jks}}$$

2. **Housing-market equilibrium**

$$G_j^{-1}(H_j) = r_j$$

Implications:

- Wages rises one-for-one with subsidy
- With elastic housing-supply schedule, partial capitalization into rents.

Static Welfare Accounting

Workers (EZ residents)

$$\Delta W^{\text{workers}} = \underbrace{N_0\,\tau}_{\text{rectangle}} + \underbrace{\tfrac{1}{2}\psi\,\tau^2 N_0}_{\text{triangle}}$$

- N_0 = baseline covered resident jobs.
- ψ = semi-elasticity of covered employment (from DiD).

Landlords (EZ housing owners)

$$\Delta W^{\text{landlords}} = H_0\,\Delta r + \tfrac{1}{2}\varepsilon_{rH}\,(\Delta r)^2 H_0$$

- H_0 = baseline housing stock in N_1.
- ε_{rH} = inverse supply elasticity.

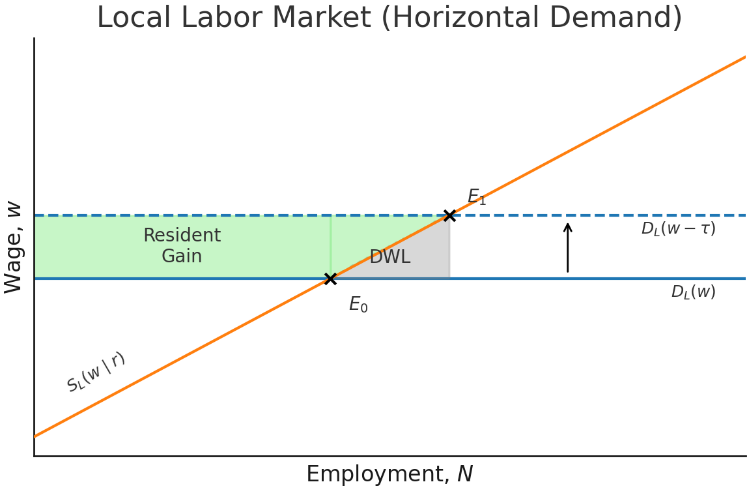
Program cost (government)

$$\text{Cost} = \tau\left[N_0 + \psi\tau N_0\right].$$

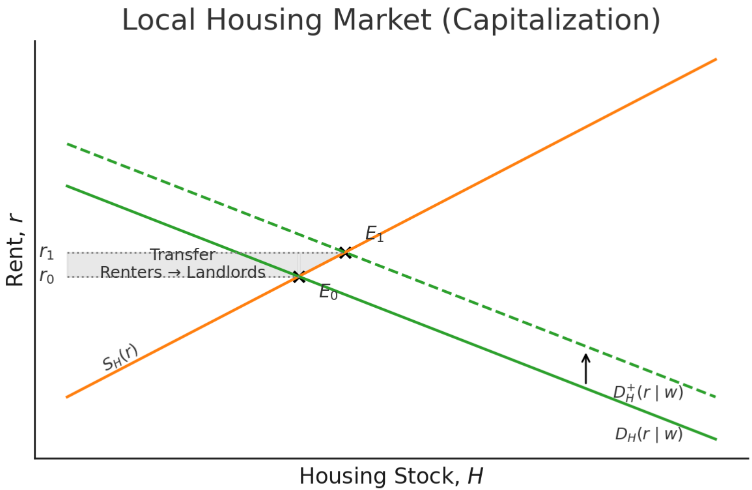
Harberger dead-weight loss

$$\boxed{\text{DWL} = \tfrac{1}{2}\psi\,\tau^2 N_0 w_0}$$ (Eq. 10 in the paper).

Labor Market, Covered Sector



Housing Market



Empirical Estimates Evaluating an Empowerment Zone: Choosing the Control Group

- **Nearby untreated neighborhoods (same city), SUTVA concerns**
  - Share shocks, infrastructure, policy climate
  - Risk of spillovers/over-effects contaminating controls
- **More distant but similarly poor areas (same city)**
  - Lower spillover risk
  - Baseline poverty or job mix may differ – diverging trends
- **Neighborhoods nominated but *not* awarded (any city)**
  - Went through comparable political process – balances hard-to-observe factors
  - May sit in different regional cycles or policy environments
- **Future awardees (eventual Zones) prior to treatment**
  - assumes no anticipatory effects or "Ashenfelter dip"

Flexible DiD Specification and ATT Estimator

Interacted regression (eq. 13):

$$\Delta Y_{tzc} = \mu_1 T_z + \overbrace{(1 - T_z)\, X'_{n(t)}\alpha_x + (1 - T_z)\, P'_c\alpha_p}^{\text{Time-change condition on } X\text{s in control tracts}} + e_{tzc} \tag{13}$$

Average Treatment Effect on the Treated (eq. 14):

$$\widehat{\mathsf{ATT}} = \underbrace{\hat{\mu}_1}_{\text{Time change in EZ}} - \underbrace{\frac{1}{N_1}\sum_{t:T_t=1}\left(X'_{n(t)}\hat{\alpha}_x + P'_c\hat{\alpha}_p\right)}_{\text{Counterfactual time change, EZ } X\text{s}} \tag{14}$$

- T_z – indicator that proposed zone z received EZ status.
- μ_1 – mean change in outcome for treated tracts (no covariate adjustment).
- $X_{n(t)}$ – distance-weighted neighborhood covariates around tract t.
- P_c – city-level controls.
- $\widehat{\mathsf{ATT}}$ – forecast-error form – compares treated mean to its counterfactual predicted by the control-sample model.

Data

- Restricted access (RDC) Longitudinal Business Database and Decennial Censuses
  - Allows analysis of small geographic units
  - Allows micro-level adjustments for demographic churn
  - Key: Allows conditioning on place of residence *and* place of work

Positive Earnings/Employment Impacts (LBD)

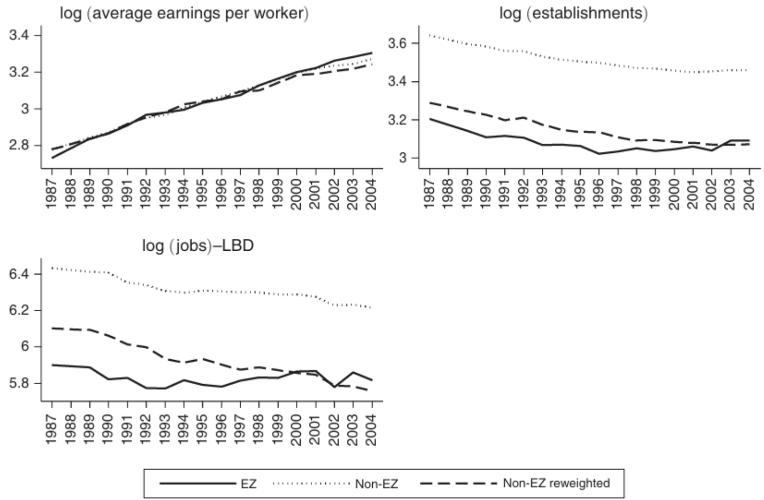


Figure 2. Jobs, Wages, and Establishments (LBD)

Positive Employment Impacts (Census)

TABLE 4—WAGE AND JOBS IMPACTS
(*Longitudinal Business Database–LBD*)

	Naïve (1)	OLS (2)	PW (3)	Observations (4)
All firms				
log (jobs)	0.122	0.179	0.213	1,651
	(0.048)*	(0.051)***	(0.072)***	
log (establishments)	0.028	0.041	0.057	1,651
	(0.027)	(0.017)**	(0.036)*	
log (average earnings per worker)	−0.018	−0.002	0.001	1,651
	(0.013)	(0.017)	(0.018)	
All firms present in 1992				
log (jobs)	0.042	0.107	0.143	1,650
	(0.044)	(0.053)	(0.068)*	
log (establishments)	−0.057	−0.022	−0.013	1,650
	(0.033)	(0.027)	(0.035)	
log (average earnings per worker)	−0.022	−0.007	0.003	1,650
	(0.020)	(0.020)	(0.027)	

Positive Earnings Impacts (Census)

TABLE 6—WAGE IMPACTS
(*Census, Journey-to-Work–JTW*)

	Unadjusted			Composition-adjusted		
	Naïve (1)	OLS (2)	PW (3)	Naïve (4)	OLS (5)	PW (6)
Panel A. Weekly wages						
log (weekly wage income of zone residents)	0.037	0.047	0.040	0.026	0.053	0.050
	(0.035)	(0.021)	(0.037)	(0.032)	(0.015)**	(0.033)
log (weekly wage income of zone workers)	−0.010	0.011	0.003	0.001	0.017	0.010
	(0.026)	(0.030)	(0.031)	(0.024)	(0.026)	(0.029)
Panel B. Weekly wages by place of residence and place of work						
log (weekly wage income of zone residents working in zone)	0.078	0.127	0.112	0.088	0.133	0.121
	(0.045)	(0.041)**	(0.055)*	(0.046)	(0.051)**	(0.051)**
log (weekly wage income of nonresidents working in zone)	−0.014	−0.015	−0.010	0.006	0.005	0.006
	(0.029)	(0.033)	(0.035)	(0.023)	(0.027)	(0.030)
log (weekly wage income of zone residents working outside zone)	0.023	0.043	0.047	0.006	0.036	0.045
	(0.028)	(0.034)	(0.031)*	(0.025)	(0.024)	(0.027)*

Capitalization into Housing Rents/Prices

Table 7—Housing Impacts

	Unadjusted			Composition-adjusted		
	Naïve (1)	OLS (2)	PW (3)	Naïve (4)	OLS (5)	PW (6)
log (rent)	0.023	0.019	0.029	0.014	0.006	0.018
	(0.032)	(0.030)	(0.032)	(0.028)	(0.026)	(0.027)
log (rent of new residents)	0.055	0.038	0.055	0.044	0.028	0.046
	(0.045)	(0.037)	(0.045)	(0.040)	(0.033)	(0.039)
log (house value)	0.370	0.281	0.311	0.371	0.281	0.317
	(0.129)*	(0.065)**	(0.142)	(0.125)*	(0.064)**	(0.138)*
log (house value of new residents)	0.208	0.143	0.142	0.246	0.164	0.171
	(0.145)	(0.104)	(0.163)	(0.131)	(0.098)	(0.151)

Returning to DWL calculation

High-end estimate of ψ:

- $\widehat{\psi} = \frac{d \ln(\text{covered sector emp})}{d\tau} = \frac{.25}{.2}$

Harberger dead-weight loss, expressed as fraction of total transfer

$$\frac{\text{DWL}}{N_0 w_0 \tau} = \frac{\frac{1}{2}\psi\,\tau^2 N_0 w_0}{N_0 w_0 \tau} = \frac{1}{2}\overbrace{\psi}^{\frac{.25}{.2}}\overbrace{\tau}^{.2} = 0.125$$

Bottom line:

- Incidence of EZ subsidy fell mainly on local workers
- Relatively small DWL associated with the transfer

Discrete Choice (Mixed Logit) Demand Systems

Discrete Choice (Mixed Logit) Demand Systems

- We do not always observe comparable locations with and without a policy of interest
  - Or the policy has never been tried

- However, we may have credible evidence on what factors drive choices
  - Sometimes from response to the policy of interest
  - Sometimes from a different source of variation

- One option in these cases is to model the individual choice process
  - Baseline choice probabilities
  - Responsiveness of choices to house prices
  - Responsiveness of choices to other attributes

Demand Estimation with BLP: What It Buys Us

- Well understood method for estimating mixed-logit discrete choice demand system
  - Berry, Levinsohn, Pakes (1995)
  - Discrete choice is natural framework for location demand
  - Key hurdle, requires a price instrument; can be combined with experimental/quasi-experimental price variation (Galiani, Murphy, and Pantano; 2015)
- **Partial equilibrium** uses:
  - May guide drawing distortion-minimizing zone boundaries (put closely substitutable neighborhoods on same side of zone boundaries)
  - Small-scale counterfactuals where rents and amenities stay fixed.
  - Pure preference recovery (e.g. valuing air quality).
- **General equilibrium** uses:
  - Combine BLP demand with housing supply curve.
  - Compute new rents, wages, sorting patterns for large-scale redesigns.

Bayer, Ferreira, and McMillan (2009)

Bayer, Patrick, Fernando Ferreira, and Robert McMillan. (2007). "A Unified Framework for Measuring Preferences for Schools and Neighborhoods." Journal of Political Economy, 115(4), 588–638.

Empirical Challenge

- Want distribution of hh preferences for **school quality** and **neighborhood attributes**
- Two methods for recovering:
  - Hedonic regressions using Boundary Discontinuity Design
  - BLP discrete choice (using similar identification strategy)
- Boundary Discontinuity Design (BDD) addresses one key endogeneity problem:

Black (1999) Figure 1

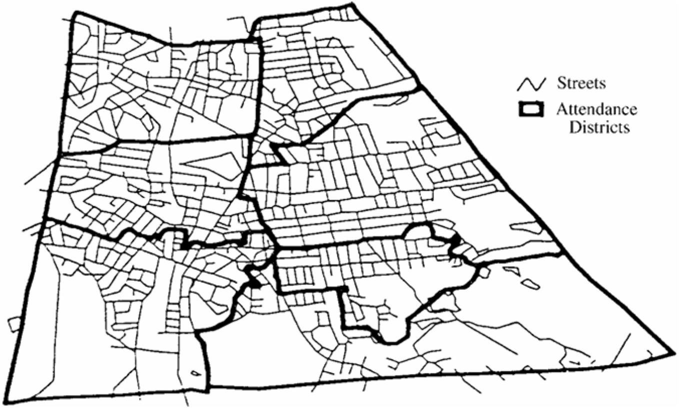
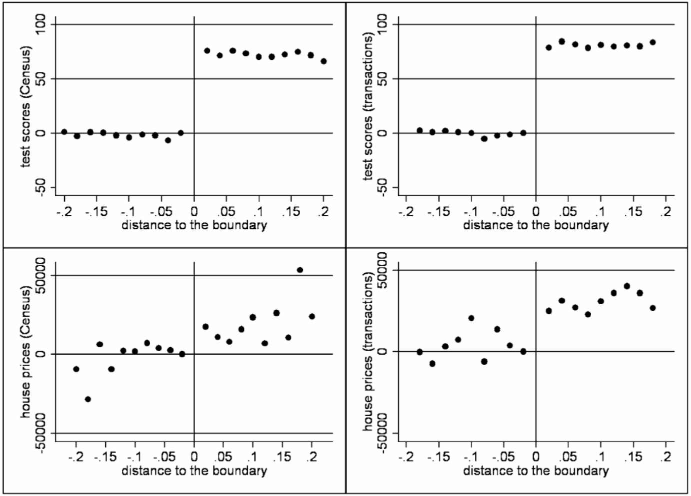


FIGURE I
Example of Data Collection for One City: Melrose Streets, and Attendance District Boundaries

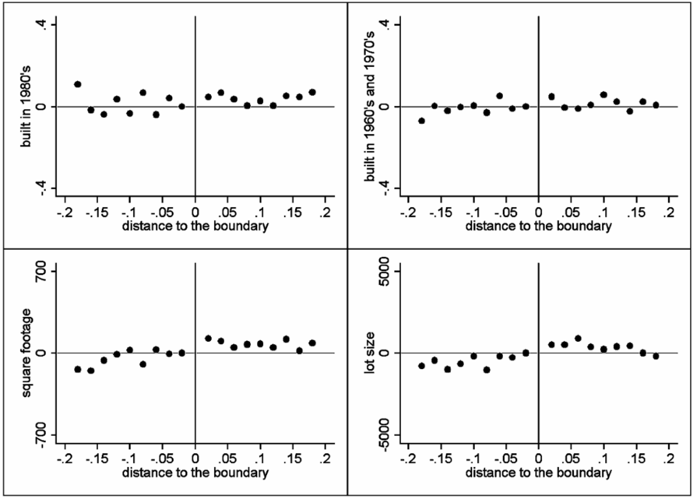
BFM: Boundary Discontinuity Design (BDD)

- Similar strategy to Black (1999), Bay Area in CA
- Attendance-zone borders generate sharp changes in test scores
- Compare houses $\leq$0.10–0.20 mile on opposite sides
- **Boundary fixed effects** absorb unobserved smooth factors
- Produces exogenous variation in:
  - Average test score
  - Neighbor composition

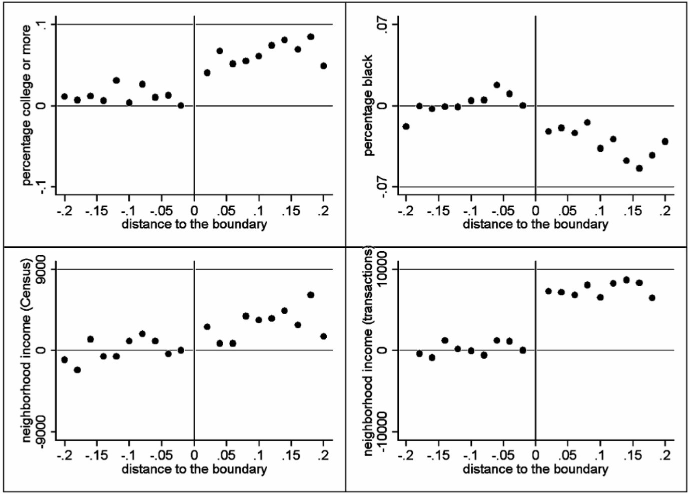
House prices jump on high-test-scores side of boundary (Fig. 1)



Housing characteristics balanced across boundaries (Fig. 3)



Demographic Composition Changes at Boundary (Fig. 4)



Hedonic Regression on Test Scores and Composition (Boundary Sample)

TABLE 3
KEY COEFFICIENTS FROM BASELINE HEDONIC PRICE REGRESSIONS

	Sample			
	Within 0.20 Mile of Boundary (N = 27,548)		Within 0.10 Mile of Boundary (N = 15,122)	
Boundary fixed effects included	No	Yes	No	Yes
	A. Excluding Neighborhood Sociodemographic Characteristics			
	(1)	(2)	(5)	(6)
Average test score (in standard deviations)	123.7	33.1	126.5	26.1
	(13.2)	(7.6)	(12.4)	(6.6)
R^2	.54	.62	.54	.62
	B. Including Neighborhood Sociodemographic Characteristics			
	(3)	(4)	(7)	(8)
Average test score (in standard deviations)	34.8	17.3	44.1	14.6
	(8.1)	(5.9)	(8.5)	(6.3)
% census block group black	−99.8	1.5	−123.1	4.3
	(33.4)	(38.9)	(32.5)	(39.1)
% block group with college degree or more	220.1	89.9	204.4	80.8
	(39.9)	(32.3)	(40.8)	(39.7)
Average block group income (/10,000)	60.0	45.0	55.6	42.9
	(4.0)	(4.6)	(4.3)	(6.1)
R^2	.59	.64	.59	.63

Turning to discrete choice / revealed preference approach

- Preferences of marginal buyers capitalize into house prices
- A complementary approach directly measures how households trade off neighborhood attributes and rent when making location choices

Random-Utility Specification

$$U_{ih} = \alpha_i X_h \; - \; \beta_i p_h \; - \; \gamma_i d_{ih} + \overbrace{\theta_{bh}}^{\text{boundary seg. FE}} + \overbrace{\xi_h}^{\text{home unobs.}} + \varepsilon_{ih}$$

- X_h: house & neighborhood traits (incl. test scores)
- p_h: monthly user cost
- d_{ih}: commute distance
- Heterogeneity: BFM allow $\alpha_i, \beta_i, \gamma_i$ to vary with Z_i
- Identification problem, in presence of sorting, regressors likely correlated with ξ_h

BLP 2-Step Estimation

$$U_{ih} = \delta_h + \overbrace{\Big(\sum_k \alpha_k \underbrace{z_{ik}}_{\text{demo. indicators}}\Big) X_h - \Big(\sum_k \beta_k z_{ik}\Big) p_h - \Big(\sum_k \gamma_k z_{ik}\Big) d_{ih}}^{\lambda_{ih}} + \varepsilon_{ih}$$

$$\delta_h = \bar{\alpha} X_h - \bar{\beta} p_h - \bar{\gamma} d_{ih} + \theta_{bh} + \xi_h$$

- Step 1: Iterate, estimating $\{\delta_h\}$ and $\{\alpha_k\}$, $\{\beta_k\}$, $\{\gamma_k\}$
- Step 2 (IV): Estimate $\bar{\alpha}$, $\bar{\beta}$, $\bar{\gamma}$, addressing endogeneity problem

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Step 1 details: Preference heterogeneity and $\{\delta_h\}$

$$U_{ih} = \delta_h + \overbrace{\Big(\sum_k \alpha_k \underbrace{z_{ik}}_{\text{demo. indicators}}\Big) X_h - \Big(\sum_k \beta_k z_{ik}\Big) p_h - \Big(\sum_k \gamma_k z_{ik}\Big) d_{ih}}^{\lambda_{ih}} + \varepsilon_{ih}$$

- Step 1: Iterate, estimating $\{\alpha_k\}$, $\{\beta_k\}$, $\{\gamma_k\}$ and $\{\delta_h\}$

  (1a) MLE for $\{\alpha_k\}, \{\beta_k\}, \{\gamma_k\}$)

  $$Pr(i \text{ chooses } h) = \frac{exp(\delta_h + \lambda_{ih})}{\sum_{h'} exp(\delta_{h'} + \lambda_{ih'})}$$

  (1b) Contraction mapping for $\{\delta_h\}$)

  $$\delta^{t+1} = \delta^t + \ln s^{\text{obs}} - \ln s^{\text{pred}}$$

- Key assumption: Common valuation of unobservables ($\theta_{ibh} + \xi_{ih} = \theta_{bh} + \xi_h \ \forall \ i$)

Step 2 details: IV Regression on $\widehat{\delta}_h$

$$\widehat{\delta}_h = \bar{\alpha} X_h - \bar{\beta} p_h - \bar{\gamma} d_{ih} + \theta_{bh} + \xi_h$$

- Endogenous regressor: p_h
- Instruments:
  - Urban analog of "BLP" instruments: Characteristics of competitor products
    - Affect eqm. prices (relevance)
    - Do not affect utility provided by good in question (exclusion)
  - Land-use & stock in rings >3 mi (supply shifters)
  - Attributes of other dwellings sharing no ξ_h

Model-Based WTP (Table 8)

TABLE 8
HETEROGENEITY IN MARGINAL WILLINGNESS TO PAY FOR AVERAGE TEST SCORE AND NEIGHBORHOOD SOCIODEMOGRAPHIC CHARACTERISTICS

		NEIGHBORHOOD SOCIODEMOGRAPHICS		
	AVERAGE TEST SCORE +1 SD	+10% Black vs. White	+10% College-Educated	Block Group Average Income +$10,000
Mean MWTP	19.69	−10.50	10.46	36.3
	(7.41)	(3.69)	(3.18)	(6.60)
Household income (+$10,000)	1.38	−1.23	1.41	.86
	(.33)	(.37)	(.21)	(.12)
Children under 18 vs. no children	7.41	11.86	−16.07	2.37
	(3.58)	(3.03)	(2.25)	(1.17)
Black vs. white	−14.31	98.34	18.45	−1.16
	(7.36)	(3.93)	(4.52)	(2.24)
College degree or more vs. some college or less	13.03	9.19	58.05	.31
	(3.57)	(3.14)	(2.33)	(1.40)

- Computed as marginal rate of substitution b/w attribute and rent (α_i/β_i)

BFM (2007): Remarks

- First urban application of the Berry, Levinsohn, Pakes (BLP) framework.
- Boundary discontinuities + supply shifters to address price endogeneity.
- Estimated BLP model supports policy simulations: predict *who substitutes from where to where* with what probability when financial incentives change (vouchers, funding shifts, tax reforms)
  - Galiani, Murphy, Pantano (2015) use MTO experiment for identification, counterfactual P.E. voucher policies
  - Davis, Gregory, Hartley, Tan (2021): Dynamic, equilibrium (prices) model to study, location conditioned voucher experiments
  - Almagro and Dominguez-Iino (2025): Dynamic equilibrium with endogenous amenities

The Low Income Housing Tax Credit (LIHTC)

- Single large federal program
- The "ideal experiment" for answering the most important LIHTC-related questions would be at the macro level
  - Ex. Does LIHTC increase the aggregate supply of housing?
- Many ways of learning how specific features of program affect specific choices or outcomes
- An attractive option is to combine causal inference with a modeling framework to extrapolate / draw broader conclusions.

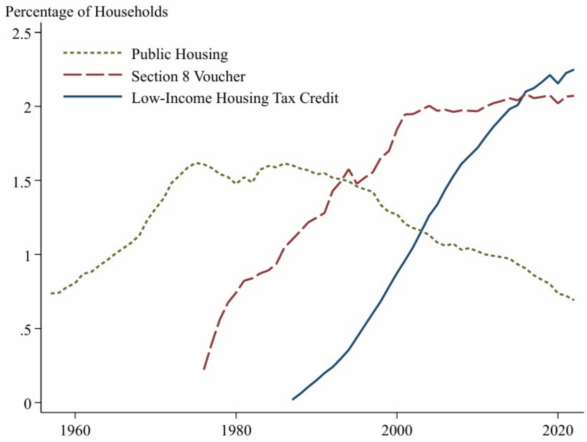
The Low Income Housing Tax Credit (LIHTC)

- Upcoming slides provide some background on LIHTC
- Discuss several LIHTC papers
  - Diamond and McQuade (2019): Amenity spillovers
  - Soltas (2024): Net supply effects
  - Cook, Li, and Binder (2024): Tradeoffs with location of LIHTC projects

The Low Income Housing Tax Credit (LIHTC)

- History:
  - Introduced in 1986 to incentivize private developers to build affordable rental housing
  - Administered by state housing finance agencies
- How It Works:
  - Developers submit bids to state-administered competitive allocation processes
  - Winners receive tax credits, which can be sold to investors to finance project
    - 9% Credit paid each year for 10 years (NPV $\approx$ 70% development cost)
  - Developers must set aside units for low-income households at capped rents
- Affordability Requirements:
  - Minimum number of units:
    - at least 20% of units for households $<$ 50% AMI (area med. income), or
    - at least 40% of units for households $<$ 60% AMI
  - Rents capped at 30% of cutoff income
  - Rents must remain "affordable" for 15-30 years

LIHTC has Become Largest Housing Assistance Program



- Source: Soltas (2024), Figure 1

LIHTC: Policy Goals and Earlier Research

- LIHTC Policy Goals:
  1. Provide social insurance
  2. Expand affordable housing supply
  3. Encourage private investment in under-served areas
  4. Promote economic and racial integration through geographic placement of LIHTC developments

- Earlier LIHTC research has focused on convenient sources of variation and local impacts on easy-to-measure outcomes
  - Baum-Snow and Marrion (2009): RDD to estimate impact of eligibility for additional 30% subsidy boost on amount of development and tract outcomes
  - Freedman and Owens (2011): Impact of LIHTC on nearby crime

Three Big Questions

1. **Supply expansion** – Does LIHTC increase the overall stock of low-income housing?

2. **Optimal placement** – Where should units be sited?
   - Resident opportunity maximization (Opportunity Atlas, school quality, jobs)
   - Size and sign of neighborhood spillovers
   - Political feasibility and local opposition (zoning, NIMBY, QAP scoring)

3. **Targeting** – Which income tiers should be served, how well targeted is the program, and what program rules affect targeting?

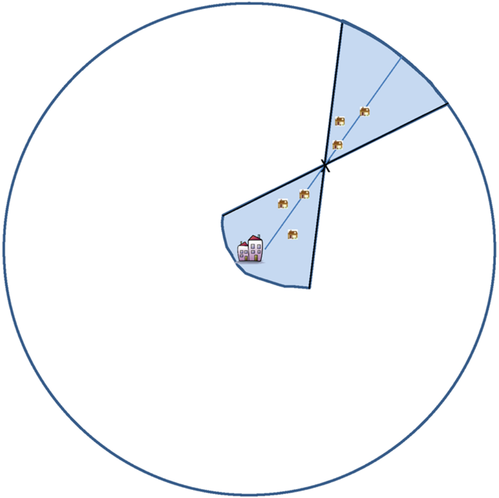
Diamond and McQuade (2019)

Diamond, Rebecca and Timothy McQuade. (2019). "Who Wants Affordable Housing in Their Backyard? An Equilibrium Analysis of Low-Income Property Development." Journal of Political Economy, 127(3), 1063–1117.

Research Questions

1. **Neighborhood spillovers**: How do LIHTC projects affect nearby house prices?
2. **Heterogeneity**: Do spillovers differ by neighborhood income and race?
3. **Welfare**: What is households' willingness to pay (WTP) for or against proximity, and the net welfare change after re-sorting?

Transaction Prices: Comparisons used by Diamond / McQuade



Empirical Price Equation

$$\ln P_{jlt} = \underbrace{\theta_l(r_{jl}, \phi_{jl})}_{\text{location F.E.}} + \underbrace{\varphi_l(\phi_{jl}, t)}_{\text{flexible time trend}} + \underbrace{m_Y(r_{jl}, \tau_{lt})}_{\text{causal effect}} + \varepsilon_{jlt} \quad (7)$$

- r_{jl}: distance from sale j to project l; ϕ_{jl}: bearing (direction)
- $\tau_{lt} = t - T_l^{\text{fund}}$: years since project l received funding
- Y: neighborhood income $\times$ minority quartile

Spatial DiD via Empirical Derivatives

Step 1: Bow-tie matching (inside vs. outside) around each transaction

$$\left(\widehat{\frac{\partial \ln P}{\partial r}}\right)_{jlt} = \sum_{k=\text{close}}^{\text{far}} \omega_k \frac{\ln P_{\text{in},t,k} - \ln P_{\text{out},t,k}}{r_{\text{in}} - r_{\text{out}}}$$

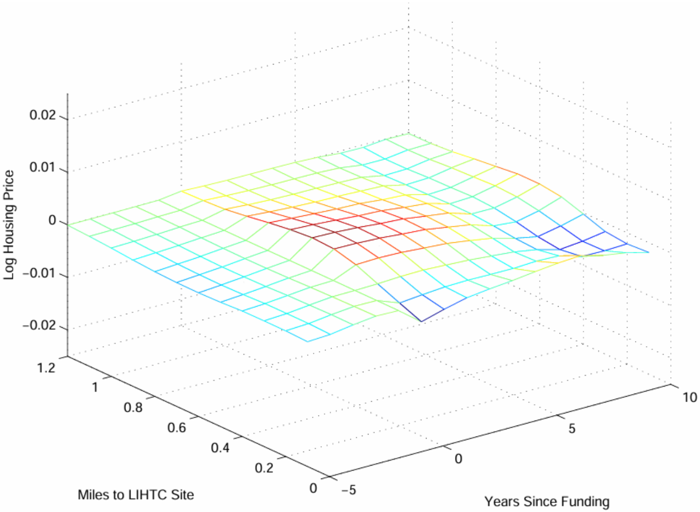
Step 2: Kernel smooth gradient at grid in (r, τ) (by neighborhood type Y)

$$\widehat{\Phi}_Y(r,\tau) = \frac{\sum_{jlt} K_r\left(\frac{r_{jl}-r}{h_r}\right) K_\tau\left(\frac{\tau_{lt}-\tau}{h_\tau}\right) \widehat{\partial \ln P/\partial r}_{jlt}}{\sum_{jlt} K_r\left(\frac{r_{jl}-r}{h_r}\right) K_\tau\left(\frac{\tau_{lt}-\tau}{h_\tau}\right)}$$

Step 3: Difference-in-Differences on the gradient

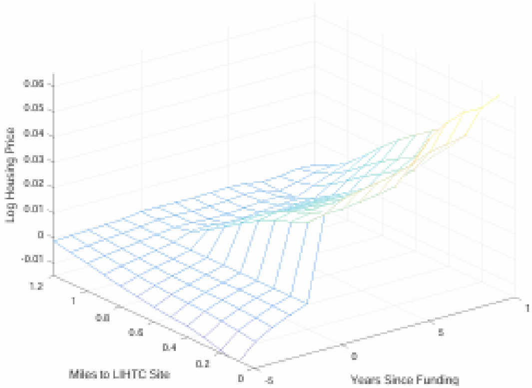
$$\frac{\widehat{\partial m'_Y}(r,\tau)}{\partial r} = \begin{cases} \widehat{\Phi}_Y(r,\tau) - \widehat{\Phi}_Y(r,-1) & \text{if } r < 1.4 \text{ miles} \\ 0 & \text{if } r \geq 1.4 \text{ miles} \end{cases}$$

Impact of LIHTC on Prices by (r, τ)

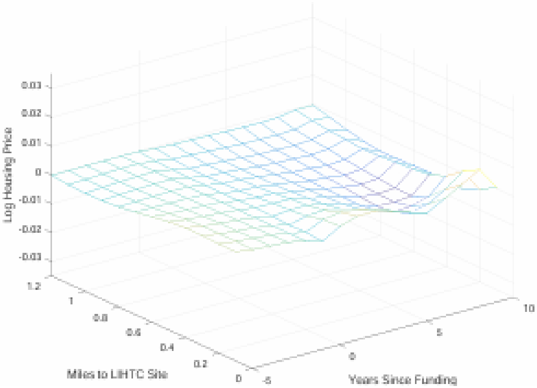


Impact of LIHTC on Prices by (r, τ), low income

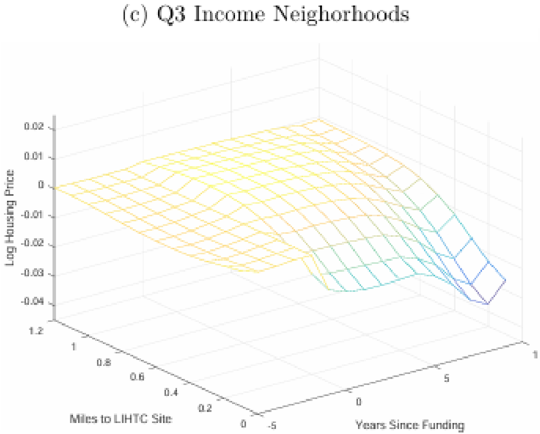
(a) Q1 Income Neighorhoods

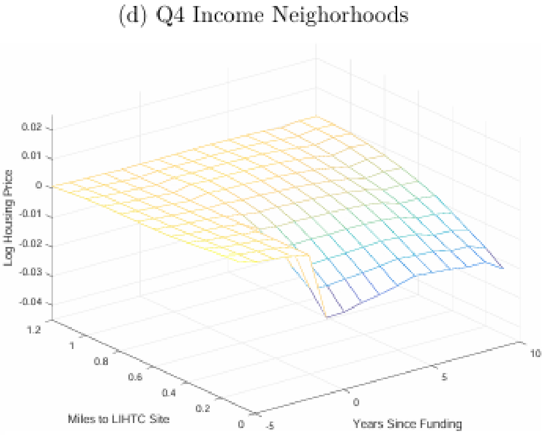


(b) Q2 Income Neighorhoods



Impact of LIHTC on Prices by (r, τ), high income





Structural Hedonic Model

$$U_{ij} = \alpha_i + \gamma_{iY}\, g_Y(R_j) + \beta \cdot X_j - P_j + \varepsilon_{ij},$$

with continuous attribute $R_j =$ distance to nearest LIHTC.

First-order condition (FOC)

$$\boxed{\gamma_{iY}\, g'_Y(R_j^*) = \left.\frac{\partial P}{\partial R}\right|_{R_j^*} = \widehat{m'_Y}(R_j^*)}$$

- γ_{iY}: household i's marginal willingness to pay (WTP) for one more mile of distance to the LIHTC (positive = disamenity).
- $g_Y(\cdot)$: functional form translating distance into perceived amenity/disamenity; varies by neighborhood type Y.
- We solve for γ_{iY} by plugging the estimated price gradient into the FOC.

Welfare Building Blocks (Notation & Intuition)

γ_{iY} **Household-specific WTP**
Positive if the project is a disamenity for that household/type; negative if amenity.

$g_Y(R)$ **Distance-utility map**
Converts physical distance R into utility units (e.g., $\log(1+R)$).

$m_Y(R)$ **Price capitalization**
Predicted *price* (or rent) change at distance R caused by the project.

R_i^{pre}, R_i^{post} Best-response locations before and after the project.

Key idea:

$$\text{Utility Gain} = \gamma_{iY}\left[g_Y(R_i^{\text{post}}) - g_Y(R_i^{\text{pre}})\right] \quad \text{vs.} \quad \text{Price Change} = m_Y\left(R_i^{\text{post}}\right) - m_Y\left(R_i^{\text{pre}}\right)$$

Welfare Components by Market Participant: Renters

1. **Renters (no move)**

$$\Delta W_i^{\mathsf{R,stay}} = \gamma_{iY}\,\Delta g_Y \; - \; \Delta m_Y$$

- Δg_Y: amenity gain/loss at the *same* unit.
- Δm_Y: rent increase/decrease they must pay. *Interpretation*: Do renters enjoy more utility than the rent hike, or vice versa?

2. **Renters (move)**

$$\Delta W_i^{\mathsf{R,move}} = \gamma_{iY}\,g_Y\big(R_i^{\mathsf{post}}\big) \; - \; m_Y\big(R_i^{\mathsf{post}}\big)$$

- They re-optimize location; old location drops out because they neither owned nor sold it.

Welfare Components by Market Participant

3. Owners (stay)

$$\Delta W_i^{\mathsf{O,stay}} = \gamma_{iY}\,\Delta g_Y \; + \; \Delta m_Y$$

- Same amenity effect as renters.
- **Capital gain** Δm_Y: owners *receive* the price appreciation (or suffer depreciation).

4. Owners (move)

$$\Delta W_i^{\mathsf{O,move}} = \Delta m_Y^{\mathsf{sell}} \; + \; \gamma_{iY}\, g_Y(R_i^{\mathsf{post}}) \; - \; m_Y\big(R_i^{\mathsf{post}}\big)$$

- $\Delta m_Y^{\mathsf{sell}}$: capital gain/loss on the *sold* home.; Remaining terms identical to renter-movers.

5. Absentee Landlords (never move)

$$\Delta W_j^{\mathsf{LL}} = m_Y\big(R_j\big)$$

- Pure asset price effect—no amenity term because they do not consume the housing.

Aggregating Welfare Around One Project

$$\begin{aligned}\Delta W_{\text{project}} = &\sum_{i \in \text{Ren. stay}} \Delta W_i^{\text{R,stay}} + \sum_{i \in \text{Ren. move}} \Delta W_i^{\text{R,move}} \\ &+ \sum_{i \in \text{Own. stay}} \Delta W_i^{\text{O,stay}} + \sum_{i \in \text{Own. move}} \Delta W_i^{\text{O,move}} \\ &+ \sum_{j \in \text{Landlords}} \Delta W_j^{\text{LL}}\end{aligned}$$

Welfare Bottom Line

- **Placement matters:**
  - Lowest-inc. quartile tracts, nearby prices and resident WTP rise, **net welfare gain**.
  - Highest-inc. quartile tracts, mild *disamenity*: small homeowner capital losses dominate, **smaller net welfare loss**.
- **Across all** $\sim 7{,}000$ **projects**, average welfare effect positive
- Suggests directing new LIHTC toward low-income, high-minority areas, other policy objective may push other way.

Soltas (2024)

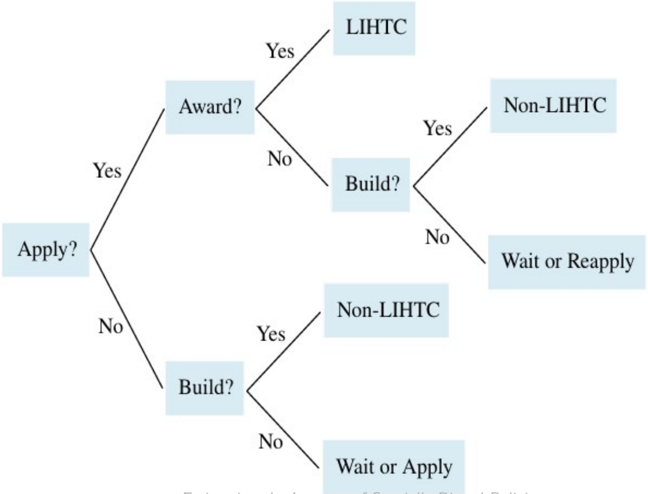
Soltas, Evan. (2024). "Tax Incentives and the Supply of Low-Income Housing." Job Market Paper, MIT Department of Economics.

Soltas (2024)

- Does LIHTC increase the supply of affordable housing?
  - Baum-Snow and Marrion (2009) show that higher subsidies increase supply of subsidized housing
  - But does LIHTC crowd out non-LIHTC housing, or shift forward development that would have happened anyways?
- Soltas provides 3 forms of causal
  - Uses LIHTC application data from 40 states linked with parcel-level dev'ment data
  - Paper's structure: Lays out structural model, presents reduced-form evidence on key facts at each model decision point
- The model's structural parameters are identified by indirect inference, targeting the reduced form estimates

Dynamic Programming Model

Figure 5: Decision Tree for the Developer



Dynamic programming representation: Application Choice

- Value function

$$V^A(\boldsymbol{s}_{it}, \boldsymbol{\varepsilon}_{it}) = \max_a \left\{\Pi^A(a, \boldsymbol{s}_{it}) + \varepsilon^A_{it}(a)\right\}, \tag{2}$$

$$\Pi^A(a, \boldsymbol{s}_{it}) = \begin{cases} p_{it}\pi_1(\boldsymbol{s}_{it}) + (1 - p_{it})\beta \mathrm{E}[V^A(\boldsymbol{s}_{it+1}, \boldsymbol{\varepsilon}_{it+1}) \,|\, \boldsymbol{s}_{it}] - \kappa(\boldsymbol{s}_{it}) & \text{if } a = 1 \\ \mathrm{E}[V^B(\boldsymbol{s}_{it}, \boldsymbol{\varepsilon}_{it}) \,|\, \boldsymbol{s}_{it}] & \text{if } a = 0. \end{cases} \tag{3}$$

  - π_1 is profit from LIHTC subsidized development

- Choice probability:

$$\log \frac{\Pr(A_{it} \,|\, \boldsymbol{s}_{it})}{1 - \Pr(A_{it} \,|\, \boldsymbol{s}_{it})} = \frac{1}{\sigma_a}\left[p_{it}\pi_1(\boldsymbol{s}_{it}) + (1 - p_{it})\beta \mathrm{E}[V^A(\boldsymbol{s}_{it+1}, \boldsymbol{\varepsilon}_{it+1}) \,|\, \boldsymbol{s}_{it}] - \kappa(\boldsymbol{s}_{it}) - \mathrm{E}[V^B(\boldsymbol{s}_{it}, \boldsymbol{\varepsilon}_{it}) \,|\, \boldsymbol{s}_{it}]\right]$$

Dynamic programming representation: Non-LIHTC Building Choice

- Value function

$$V^B(\boldsymbol{s}_{it}, \boldsymbol{\varepsilon}_{it}) = \max_b \left\{ \Pi^B(b, \boldsymbol{s}_{it}) + \varepsilon^B_{it}(b) \right\}, \tag{4}$$

$$\Pi^B(b, \boldsymbol{s}_{it}) = \begin{cases} \pi_0(\boldsymbol{s}_{it}) & \text{if } b = 1 \\ \beta \mathrm{E}[V^A(\boldsymbol{s}_{it+1}, \boldsymbol{\varepsilon}_{it+1}) \mid \boldsymbol{s}_{it}] & \text{if } b = 0. \end{cases} \tag{5}$$

  - $\pi_0(s_{it})$ is profit from private development

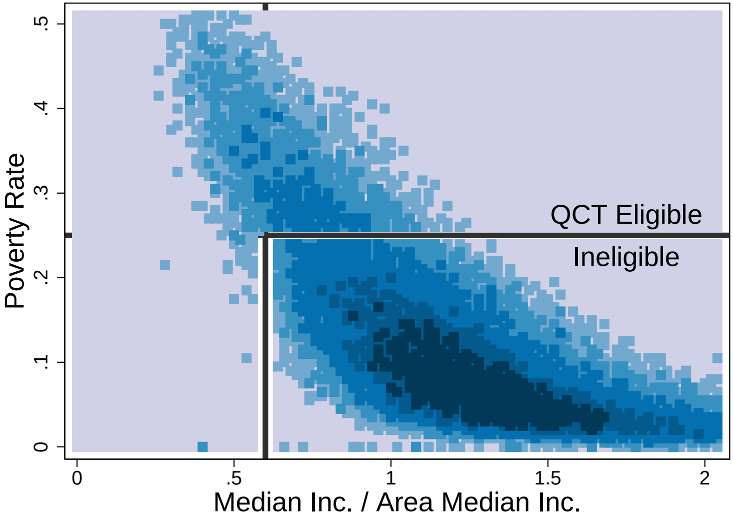
- Choice probability:

$$\log \frac{\Pr(B_{it} = 1 \mid \boldsymbol{s}_{it})}{1 - \Pr(B_{it} = 1 \mid \boldsymbol{s}_{it})} = \frac{1}{\sigma_b} \left[\pi_0(\boldsymbol{s}_{it}) - \beta \mathrm{E}[V^A(\boldsymbol{s}_{it+1}, \boldsymbol{\varepsilon}_{it+1}) \mid \boldsymbol{s}_{it}] \right], \tag{8}$$

Causal Effect of LIHTC Subsidy on Applications

- Standard LIHTC subsidy covers 70% of qualifying development costs
- In Qualifying Census Tracts (QCT), subsidy is 30% higher (91% total subsidy)
- QCT rules:
  - Tract is a QCT if: $\underline{\text{tract pov.} > 25\%}$ **or** $\underline{\text{tract median income} < .6\times(\text{Area Median})}$
  - Some other caveats
- Two identification strategies:
  - Event study when QCT status changes with new Census/ACS
  - RD at eligibility cutoffs

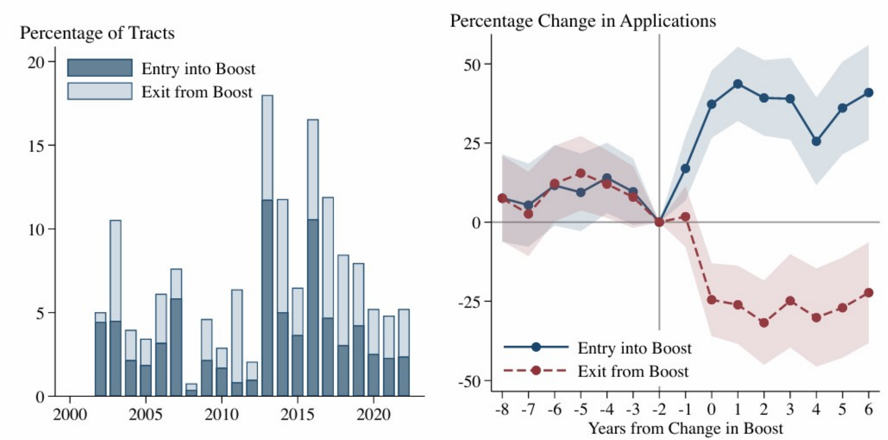
QCT – Cutoffs



QCT Eligible
Ineligible
Poverty Rate
0
.1
.2
.3
.4
.5
0
.5
1
1.5
2
Median Inc. / Area Median Inc.

QCT – Event Study

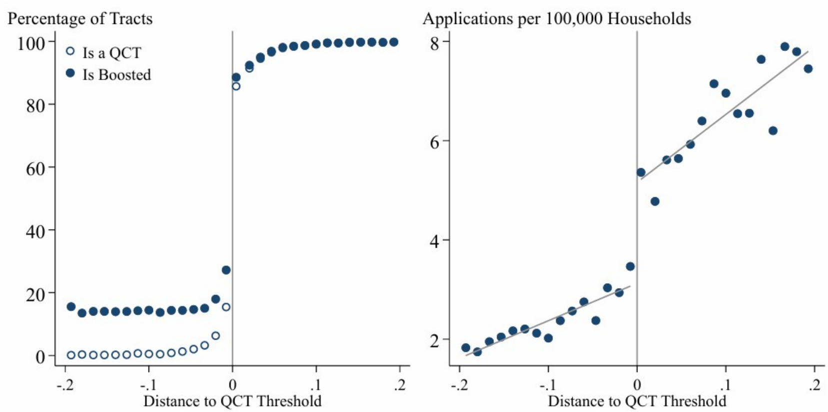
Figure 8: Application Supply Responses to Changes in Eligibility for Basis Boost



Notes: This figure plots, in the left panel, the share of Census tracts which enter or exit boost in years from 2001 to 2022. The right panel plots event-study coefficients from Equation 10 which allow for heterogeneous effects of entry and exit from boost. I include state–year fixed effects as the controls. The bands show pointwise 95-percent confidence intervals, with standard errors clustered by tract.

QCT – RDD

Figure 9: Application Volume Around the Qualified Census Tract Threshold



Notes: In the left panel, this figure shows that the probabilities that a tract is designated a Qualified Census Tract (QCT) and is boosted both rise discontinuously in its distance to the QCT threshold. In the right panel, this figure shows that the count of LIHTC applications per 100,000 households living in the Census tract (in the year of application) also jumps at the QCT threshold. In both panels, the running variable is a distance defined with respect to tract rank within

Takeaway 1:

- Application probability is very responsive to subsidy generosity
- In terms of the model:
  - Subsidized development payoff π_1 is somewhat close to priv. development payoff π_0
  - σ_A is modest in size, ($\frac{1}{\sigma_A}$ governs elasticity)

Measurement: Long-run Effects of LIHTC Awards on Housing Supply

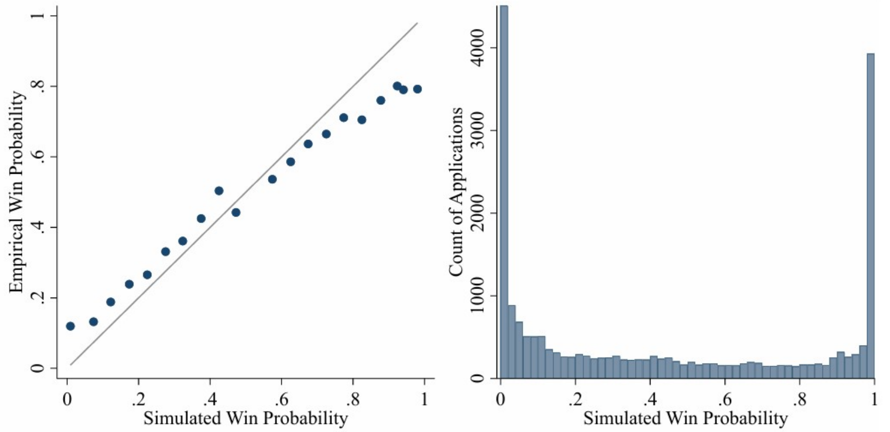
- Event study (conditional on estimated win probability – e.g. propensity score)

$$B_{it} = \alpha_i + \alpha_t + \sum_k [\beta_k Win_{it-k} + \gamma_k Lose_{it-k} + f_k(\widehat{p}_{it-k})] + e_{it}$$

  - $\widehat{p}_{it}$ construction required very serious data work.
    - Looked at application scoring each state-year (40 states)
    - Figured out the award rule
    - Simulates win probabilities by redrawing application choices of all other parcels and applying the award rule

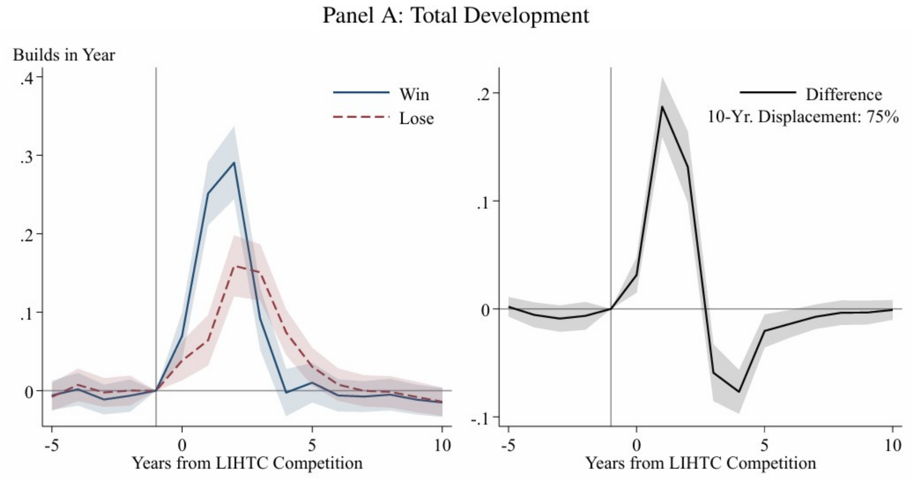
Estimated Propensity Scores

Figure 2: Calibration and Distribution of Simulated Win Probabilities

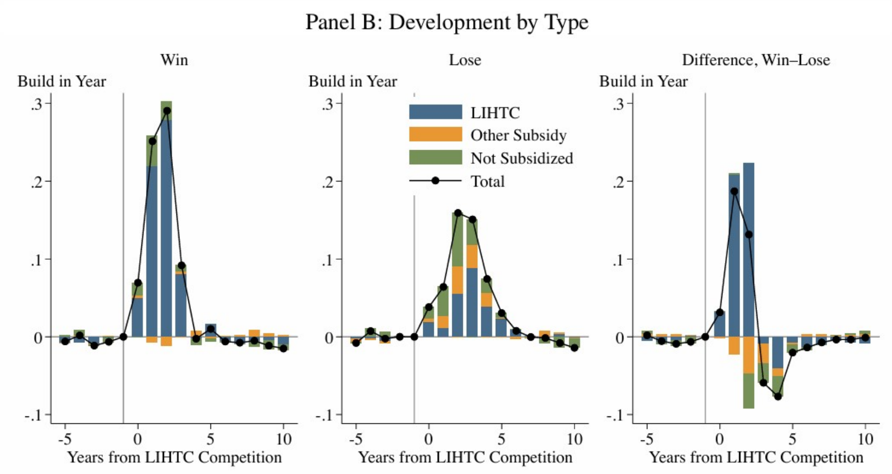


Notes: This figure plots, in the left panel, a binned scatterplot of empirical versus simulated probabilities of winning a tax credit. In the right panel, the figure plots a histogram of the simulated win probabilities. The data is split into twenty equal-interval bins in the left panel and fifty equal-interval bins in the right panel.

Event Study Estimates – Total Development



Event Study Estimates – by type of development



Takeaway 2:

- Most parcels have a profitable building option
- In terms of the model, $\pi_0(s_{it}) > 0$ for many i

Developer Preferences for Rent – for Understanding Incidence

- Finds Iso-Value combinations of Δp_{it} and Δr_{it}

$$\Pi^A(a, s_{it}) = \begin{cases} p_{it}\pi_1(s_{it}) + (1 - p_{it})\beta \mathrm{E}[V^A(s_{it+1}, \varepsilon_{it+1}) \mid s_{it}] - \kappa(s_{it}) & \text{if } a = 1 \\ \mathrm{E}[V^B(s_{it}, \varepsilon_{it}) \mid s_{it}] & \text{if } a = 0. \end{cases} \tag{3}$$

$$\Delta V^A(s_{it}) \approx \Delta p_{it} \left[\pi_1(s_{it}) - (1 - p_{it})\beta \mathrm{E}[V^A(s_{it+1}, \varepsilon_{it+1}) \mid s_{it}]\right] + p_{it} \left[\Delta r_{it} + \Delta e_{it}\right], \tag{11}$$

- Derives linear probability model of choice to include a rent reduction:

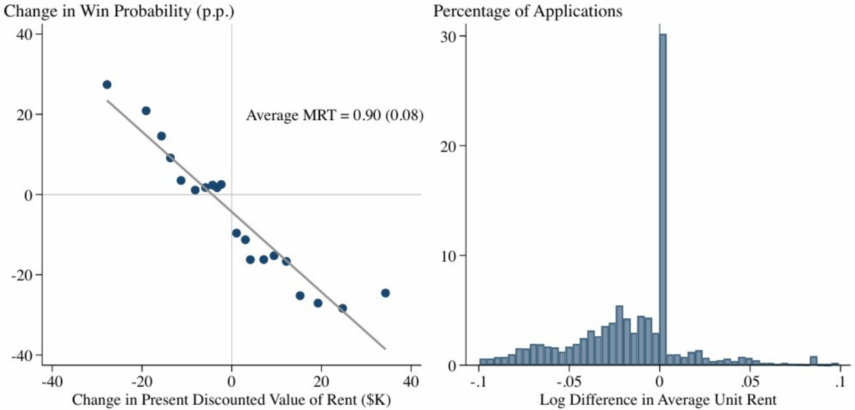
$$\pi_1(s_{it}) = (1 - p_{it})\beta \mathrm{E}[V^A(s_{it+1}, \varepsilon_{it+1}) \mid s_{it}] - \frac{p_{it}(\Delta r_{it} + \Delta e_{it})}{\Delta p_{it}}. \tag{12}$$

$$\Delta u_{ij} = \beta_1 \Delta p_i(r_{ij}) + \beta_2 \Delta \log r_{ij} + \Delta e_{ij}, \tag{13}$$

  - Interested in ratio β_2/β_1 (MRS between rent and award probability)

Data patterns captured by linear probability model of rent adjustments

Figure 10: Trade-Off Between Win Probability and Rental Income



Notes: The left panel is a binned scatterplot of two dimensions of deviations from the applications that developers actually submitted. The horizontal axis is the present value rent difference in thousands of dollars per unit. The vertical

Takeaway 3:

Table 3: Estimating Valuations from Bidding Behavior

	(1) OLS	(2) IV	(3) Cond. Logit.	(4) + Ctrl. Funct.
Win Probability	0.416***	1.708***	1.278***	6.423***
	(0.021)	(0.042)	(0.071)	(0.195)
Log Average Rent	0.620***	2.900***	1.826***	10.249***
	(0.049)	(0.098)	(0.147)	(0.395)
Applications	6,785	6,785	6,779	6,779
Marg. Rate of Substitution	0.923	1.051	0.884	0.987
	(0.040)	(0.021)	(0.039)	(0.019)
Mean Win Value Per Unit	$54,957	$48,292	$57,385	$51,385
	(2,441)	(1,022)	(2,608)	(1,040)
Developer Incidence Share	0.456	0.401	0.476	0.427
	(0.021)	(0.010)	(0.023)	(0.010)

- Developer's incidence $40+\%$

Structural Estimation

- Parameters: $\theta = \Big[\overbrace{\pi_0(s_{it}), \pi_1(s_{it})}^{\text{development payoffs}}, \underbrace{\kappa(s_{it})}_{App.costs}, \overbrace{\sigma_A, \sigma_B}^{\text{shock S.D.'s}}, \underbrace{F(X_i)}_{\text{distribution of parcel X's}} \Big]$

$$\widehat{\theta} = \text{arg min}_\theta \; [\widehat{\beta} - \tilde{\beta}]' \; \Sigma^{-1} \; [\widehat{\beta} - \tilde{\beta}]$$

- where $\widehat{\beta}$ are target empirical moments, and $\tilde{\beta}$ are analogs from model-simulated data

Counterfactual Policy Experiments

1. LIHTC without rationing/competition: All eligible projects receive subsidies
   - Timing of construction changes, but few additional units due (just more crowd out)
2. Optimal Subsidy Design: Subsidies are allocated to maximize welfare
   - Welfare increases by improving the geo. targeting, but crowd out limits gains
3. Voucher-Based System: LIHTC replaced by a demand-side voucher program
   - Vouchers achieve similar household benefits but at 25% lower fiscal cost
   - Avoid inefficiencies from developer profit capture and application costs
4. Increased LIHTC Subsidy Generosity
   - Leads to higher rents and dev. profits, but little change in net new housing stock

Cook, Li, and Binder (2024)

Cook, Cody, Pearl Z. Li, and Ariel J. Binder. Where to build affordable housing?: Evaluating the tradeoffs of location. Rochester, NY: US Census Bureau, Center for Economic Studies, 2024.

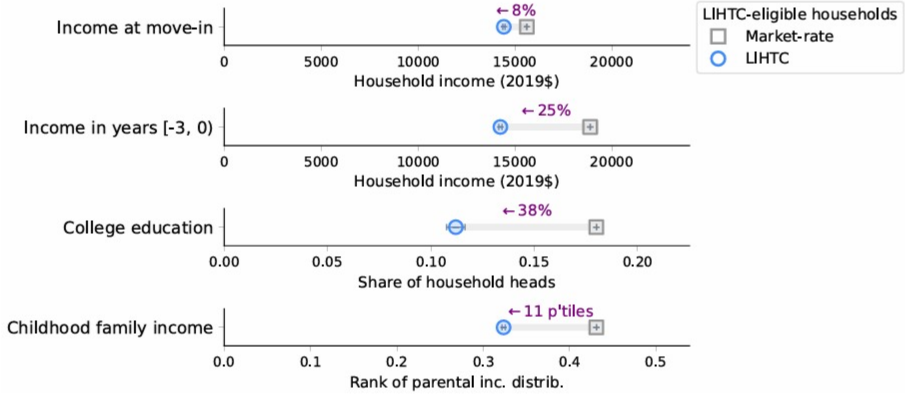
Cook, Li, and Binder

- Assembles highest quality data on LIHTC resident population.
  - Tax records, including migration histories
  - American Community Survey (sample) – detailed demographics
  - LIHTC addresses

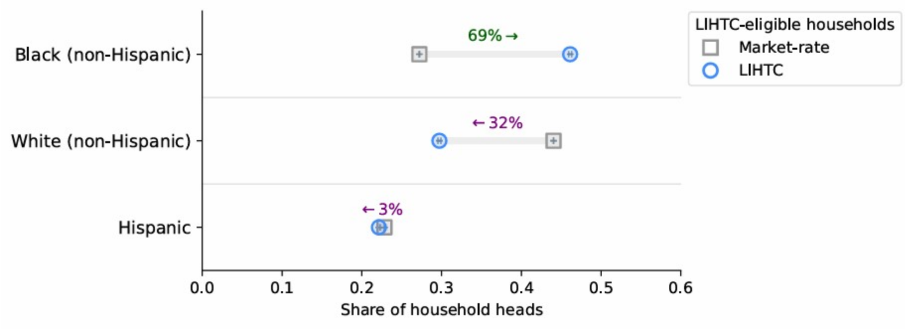
- Documents two key motivating facts:
  1. Self-targeting: LIHTC residents more disadvataged than average eligible population
  2. Recent initiative, steering LIHTC units to affluent n'hoods, weakens targeting

- Develops a structural neighborhood choice model:
  1. Households choose n'hood and whether to live in market rate or LIHTC
  2. LIHTC units are oversubscribed, rationed by lotteries
  3. More affluent eligible households only apply for LIHTC in more affluent neighborhoods, while poorer households apply more widely
     - Less affluent houeshold are crowded out from LIHTC units in affluent neighborhoods

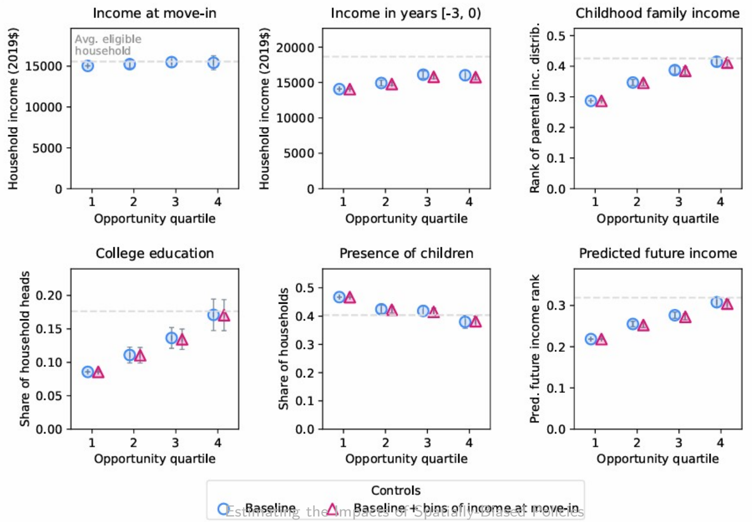
Cook, Li, and Binder – Key fact #1: Overall LIHTC is well-targeted



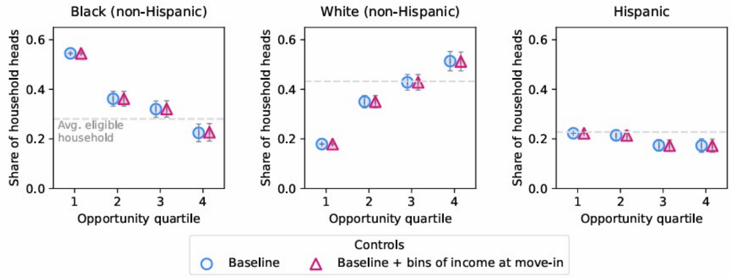
Cook, Li, and Binder – Key fact #1: Overall LIHTC is well-targeted (cont.)



Cook, Li, and Binder – Key fact #2: Targeting is worse in affluent n'hoods



Cook, Li, and Binder – Key fact #2: Targeting is worse in affluent n'hoods (cont.)



Model Overview

- Key data limitation: do not observe applications
- Two-stage, static residential-choice model within a city.
  1. **Application stage:** eligible households decide which affordable units to apply to.
  2. **Allocation stage:** developers ration units with a weighted lottery; losers choose among market-rate options.
- Supply of LIHTC units is fixed; market-rate rents clear the rest of the market.
- Purpose: disentangle *household demand* from *developer discretion* in shaping tenant composition.

Estimation Strategy

1. **Step 1 – Market-rate demand (Bayer–Ferreira–McMillan logit):** use market renters to estimate γ, β, κ; control for endogeneity with **Waldfogel-style demographic-shift instrument**.

2. **Step 2 – GMM for LIHTC-specific terms:** given Step 1 parameters, estimate α and lottery weights φ
   - match moments on move-ins *and* move-outs
   - weighting matrix based on bootstrap covariance.

Counterfactual Exercises (Highlights)

- Shift a new 82-unit LIHTC project from bottom- to top-quartile tracts:
  - Tenant surplus $\uparrow \$151$ per unit-month
  - Implicit subsidy cost $\uparrow \$458$ per unit-month
  - Share Black/Hispanic tenants $\downarrow$ 42 pp
- Post-construction levers (lower income limits, income-based rents, local-resident priority) move outcomes **far less** than the location decision.

Externalities

Fu and Gregory (2019)

Fu, Chao and Jesse Gregory. (2019). "Estimation of an Equilibrium Model with Externalities: Post-Disaster Neighborhood Rebuilding." Econometrica, 87(2), 387–421.

Welfare Effects of Natural Disaster Relief: Two Questions

1. Should uninsured homeowners be bailed out?
   - Insurance vs. moral hazard tradeoff

2. Optimal grant structure?
   - Unconditional compensation?
   - *Or subsidies to rebuild*:
     - What is the excess burden from distorting location choices?
     - How large are any positive spillovers for inframarginal neighbors?

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Case Study: Hurricane Katrina

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- August 29, 2005: Katrina makes landfall
- August 31, 2005: Flood waters cover 80% of New Orleans
- Renders $2/3$ of housing stock uninhabitable

Louisiana Road Home Program:

- Federal block grant ($\approx$\$10B) to Louisiana $\longrightarrow$ grants for homeowners
- "Road Home" Grant = ("value of damages") - (private insurance)
    - Discontinuous formula for assigning ("value of damages")
- Recipients could rebuild or relocate
    - Relocation option: HH turns its home/property over to state

Research Design

- Develop an equilibrium model of neighbors' rebuilding choices
- Estimate causal "treatment effects" with an RDD:
  - Private financial elasticities
  - Rebuilding spillovers
- Estimate the model by indirect inference, and perform counterfactual experiments

Presentation Order

1. Data and reduced form evidence
2. Equilibrium model
3. Estimation and counterfactual policy experiments

Data

Data

- Orleans Parish Assessor's Office administrative records
  - Timing of home sales and repairs
- Road Home program administrative records
  - Grant offers
  - Participation status
  - Damage estimates, private insurance
- Other datasets
  - Block-level flood exposure (FEMA)
  - 2000 Decennial Census
  - Displaced New Orleans Residents Survey/ACS
  - NY Fed's Consumer Credit Panel

Data

- Sample restricted to:
  - Homes that were owner occupied in 2005
  - Census blocks with more than 5 owner occupied homes in August 2005
- Sample includes 60,175 households

Quasi-experiment: Road Home grant discontinuity

Quasi-experiment: Road Home grant discontinuity

- Road Home grant offer formula:

$$\text{R. H. Grant} = \min\Big(\textbf{[Damage Value]} - \text{[Insurance Payout]} \;;\; \$150\text{k}\Big)$$

- Two methods for valuing home damages:
  - **Repair cost:** Item-by-item inspection × item values
  - **Replacement cost:** Home's square footage × $130

$$\textbf{[Damage Value]} = \begin{cases} \textbf{[Repair Cost]} & \text{if } \dfrac{\text{[Repair Cost]}}{\text{[Replacement Cost]}} < 51\% \\ \textbf{[Replacement Cost]} & \text{if } \underbrace{\dfrac{\text{[Repair Cost]}}{\text{[Replacement Cost]}}}_{\text{Damage Fraction}} \geq 51\% \end{cases}$$

RDD Estimates: Opportunity Cost of Relocating

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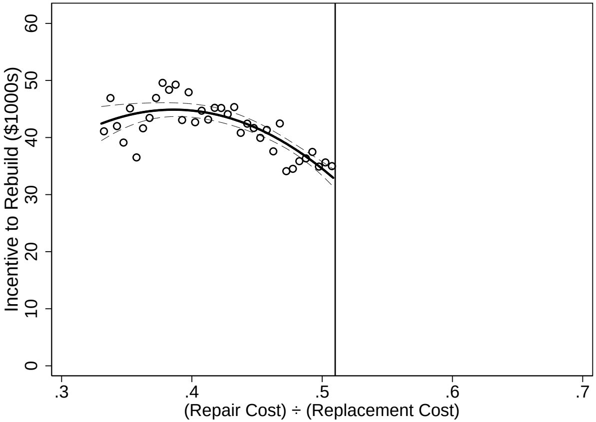
$$\text{Opp. Cost} \approx \text{Min}\left(\underbrace{\text{As-is Property Value}}_{\text{Foregone w/ RH grant}} ; \underbrace{\text{Road Home Grant Offer}}_{\text{Foregone w/ private sale}} \right)$$



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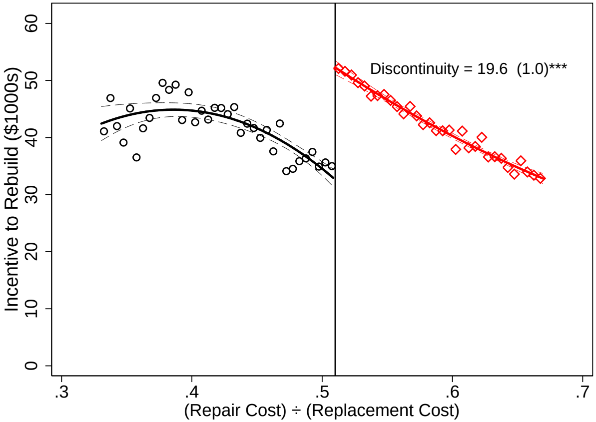

RDD Estimates: Home Rebuilt by Pre-Katrina Owner

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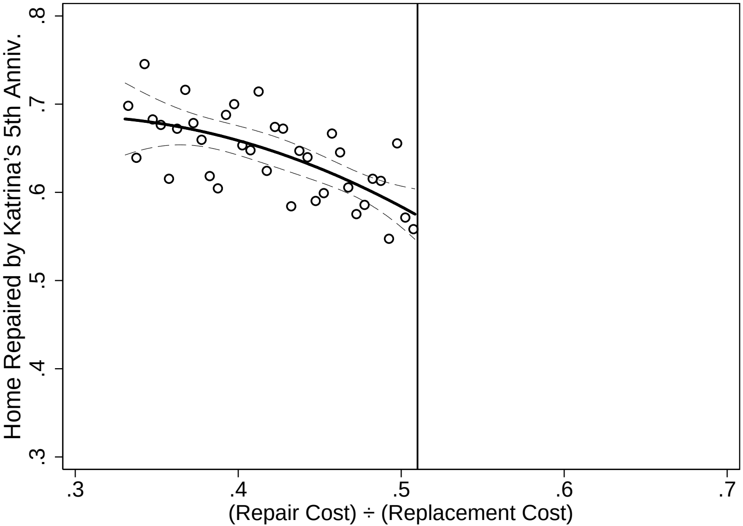

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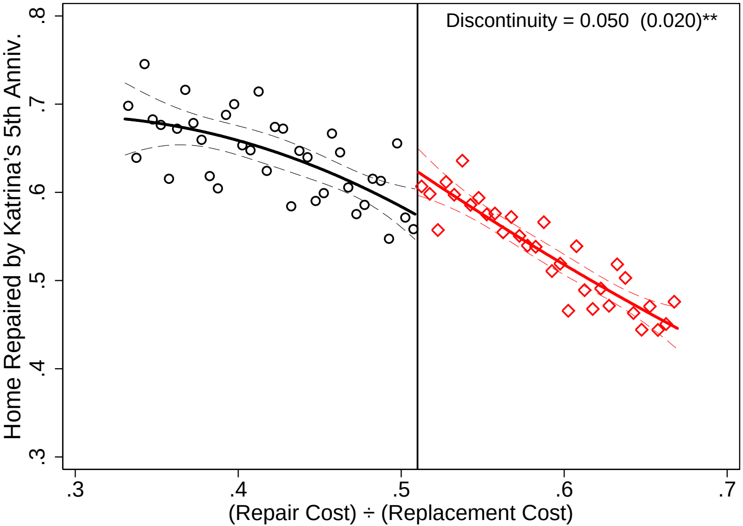

RDD Validity: McCrary Test with Pre-Appeal Inputs

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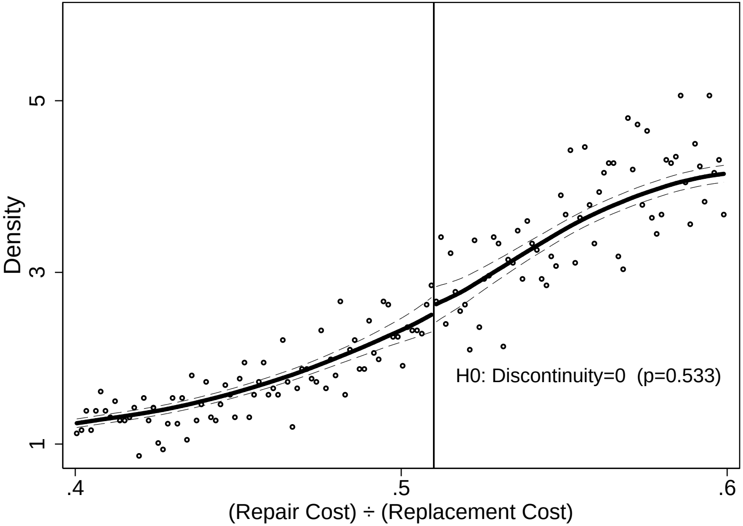

RDD Validity: Covariate Balance

RDD Validity: Covariate Balance

Background Variables Just Above/Below 51% Home Damage

	Left Limit		Right Limit		p-value: (H0: L=R)
Fraction of block homes undamaged	0.048	(0.004)	0.046	(0.004)	**0.698**
Fraction black (Census block):	0.713	(0.011)	0.717	(0.01)	**0.768**
Fraction college (Census block group)	0.474	(0.005)	0.480	(0.005)	**0.342**
Poverty rate (Census tract)	0.198	(0.003)	0.200	(0.003)	**0.774**
Average neighborhood credit score	636.7	(1.4)	638.4	(1.4)	**0.425**
Flood depth (Census block)	3.14	(0.06)	3.17	(0.05)	**0.753**

RDD Validity: Covariate Balance (continued)

	Left Limit		Right Limit		p-value: (H0: L=R)
Fraction college < 10th city-wide pctile	0.088	(0.009)	0.098	(0.008)	**0.373**
Fraction college < 25th city-wide pctile	0.215	(0.012)	0.213	(0.011)	**0.910**
Fraction college < 50th city-wide pctile	0.491	(0.015)	0.484	(0.013)	**0.729**
Fraction college < 75th city-wide pctile	0.845	(0.013)	0.816	(0.012)	**0.094**
Fraction college < 90th city-wide pctile	0.943	(0.009)	0.946	(0.008)	**0.778**
Poverty < 10th city-wide pctile	0.052	(0.009)	0.054	(0.008)	**0.875**
Poverty < 25th city-wide pctile	0.194	(0.013)	0.194	(0.011)	**0.979**
Poverty < 50th city-wide pctile	0.522	(0.015)	0.523	(0.014)	**0.974**
Poverty < 75th city-wide pctile	0.788	(0.012)	0.790	(0.011)	**0.916**
Poverty < 90th city-wide pctile	0.924	(0.009)	0.909	(0.008)	**0.192**
Average credit score < 10th city-wide pctile	0.103	(0.009)	0.119	(0.008)	**0.177**
Average credit score < 25th city-wide pctile	0.260	(0.013)	0.260	(0.012)	**0.992**
Average credit score < 50th city-wide pctile	0.567	(0.015)	0.535	(0.013)	**0.116**
Average credit score < 75th city-wide pctile	0.830	(0.013)	0.831	(0.011)	**0.929**
Average credit score < 90th city-wide pctile	0.958	(0.009)	0.949	(0.008)	**0.462**
Flooding < 2 feet	0.293	(0.012)	0.288	(0.011)	**0.772**
Flooding 2-4 feet	0.409	(0.014)	0.411	(0.013)	**0.910**
Flooding 4-6 feet	0.222	(0.012)	0.229	(0.011)	**0.676**
Flooding > 6 feet	0.077	(0.010)	0.072	(0.009)	**0.729**

RDD Validity: Neighbors' Incentives

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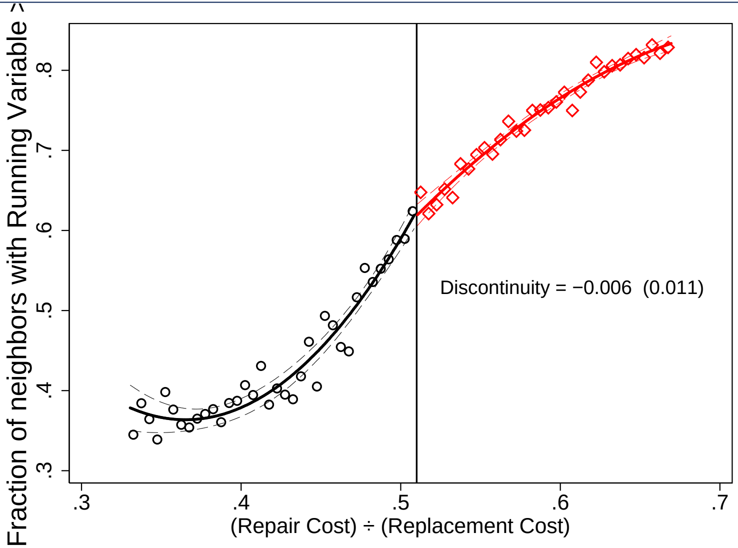
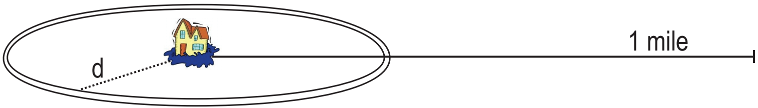


Rebuilding Spillovers by Distance

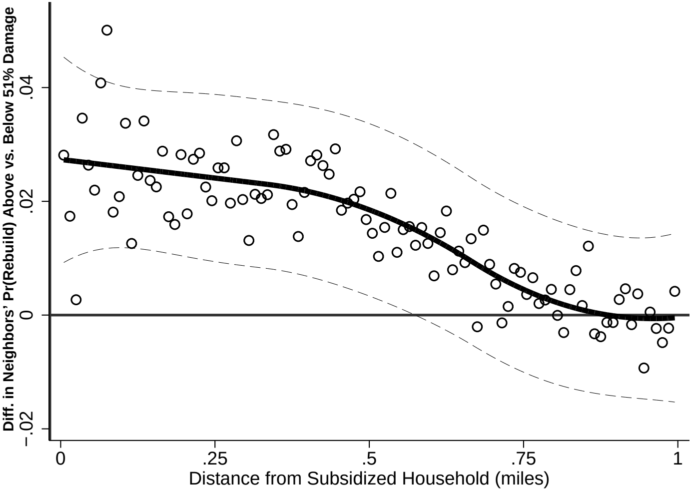
- Forcing variable: $R_i = DamageFraction_i - .51$
- Within narrow distance bins d $= 0, .01, ..., 1$ miles, estimate:

$$\mu_i^{(d)} \;=\; \mu + \Delta^{(d)} \times 1_{R_i>0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R_i>0} + a_4 R_i^2 \times 1_{R_i>0} + e_i$$



Return

Rebuilding Spillovers by Distance

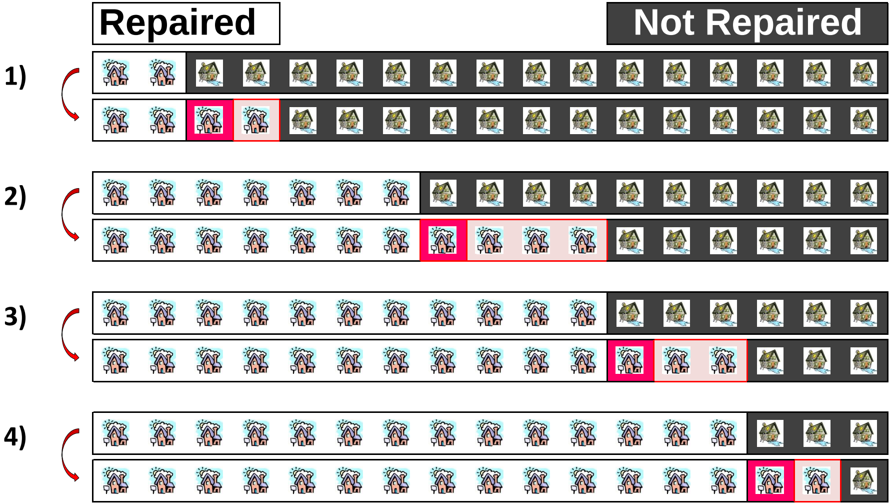


Return

Strategy for Identifying Spillover Effects

Strategy for Identifying "Shape" of Spillover Effects

Strategy for Identifying "Shape" of Spillover Effects



Impact on Neighbors' Rebuilding Choices

- Average rebuilding:

$$\mu_{j(i),-i} \quad = \quad \overline{\mu} + \overline{\Delta} \times 1_{R_i > 0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R_i > 0} + a_4 R_i^2 \times 1_{R_i > 0} + e_i$$

- Neighbors' rebuilding thresholds:

$$\begin{aligned}
1(\mu_{j(i),-i} > .1) \quad &= \quad S^{(10)} + \Delta^{(10)} \times 1_{R_i > 0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R_i > 0} + a_4 R_i^2 \times 1_{R_i > 0} + e_i \\
1(\mu_{j(i),-i} > .2) \quad &= \quad S^{(20)} + \Delta^{(20)} \times 1_{R_i > 0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R_i > 0} + a_4 R_i^2 \times 1_{R_i > 0} + e_i \\
&\vdots \\
1(\mu_{j(i),-i} > .9) \quad &= \quad S^{(90)} + \Delta^{(90)} \times 1_{R_i > 0} + a_1 R_i + a_2 R_i^2 + a_3 R_i \times 1_{R_i > 0} + a_4 R_i^2 \times 1_{R_i > 0} + e_i
\end{aligned}$$

Spillovers by Distance Return

Block Neighbors' Rebuilding Above/Below 51% Damage

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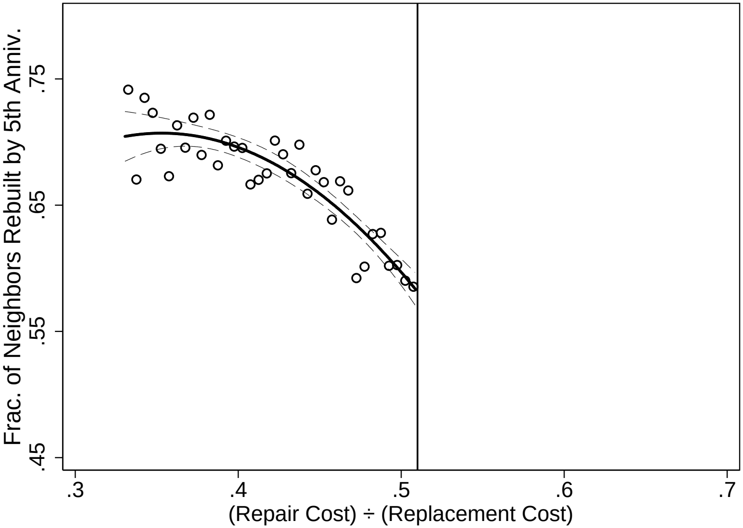
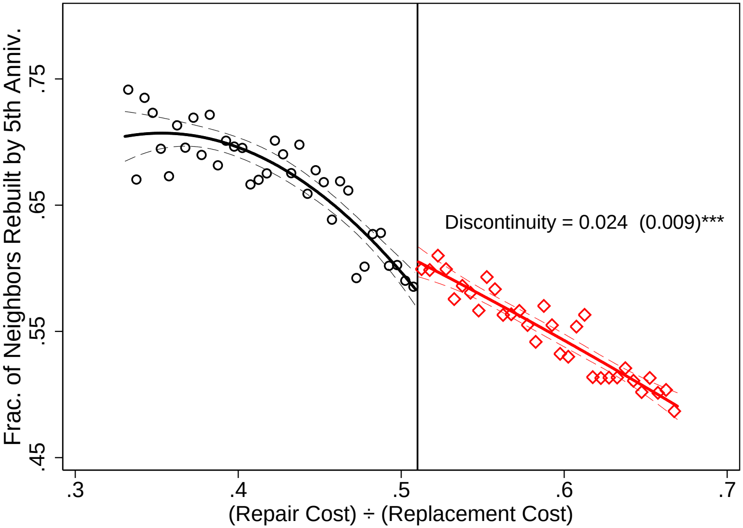


Block Neighbors' Rebuilding Above/Below 51% Damage



Rebuilding-Rate CDF Above/Below 51% Home Damage

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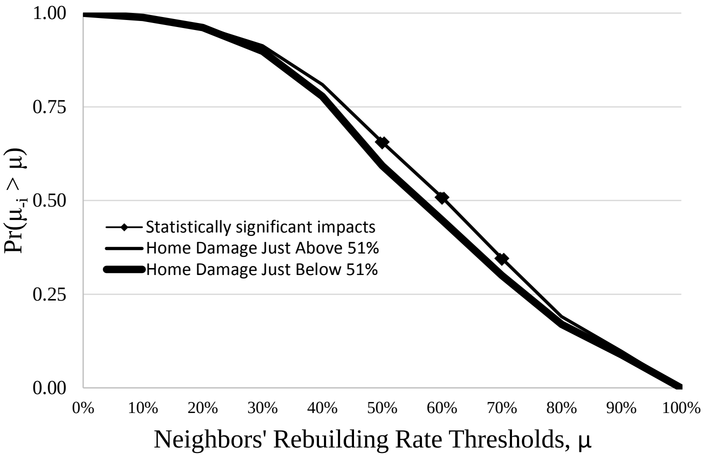

Model

Model: Framework

- Households $i = 1, ..., I$
- Blocks $j = 1, ..., J$. Spillovers possible within blocks.
- Timing
  - $t = 0, ..., T, ...$ (each period is 1 year)
  - Katrina occurs at t=0
  - Households choose when to rebuild, if ever
  - Returning/rebuilding is one action and "absorbing" until t=8 (consistent w/ timing of RH no-selling rule)

Model: Preferences

$$u_{it}(\mu_{j(i),t}; d_{it}) = \begin{cases} \ln(c_{it}) & \text{if } d_{it} = 0 \\ \underbrace{\ln(c_{it})}_{\text{consumption}} + \underbrace{\overbrace{\delta_t + z'_{j(i),t}\gamma}^{\text{observable}} + \overbrace{b_{j(i)}}^{\text{unobs.}}}_{\text{exogenous amenities}} + \underbrace{g(\mu_{j(i),t})}_{\text{spillovers}} + \underbrace{\eta_i}_{\text{hh attachment}} & \text{if } d_{it} = 1 \end{cases}$$

$$d_{it} = \mathbf{1}[\text{household } i \text{ rebuilt by } t] \quad ; \quad \mu_{jt} = \frac{1}{I_j} \sum_{i \in j} d_{it}$$

Model: Preferences

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$$d_{it} = \mathbf{1}[\text{household } i \text{ rebuilt by } t] \quad ; \quad \mu_{jt} = \frac{1}{I_j}\textstyle\sum_{i \in j} d_{it}$$

$$\eta_i \sim N(0, \sigma_\eta) \quad ; \quad b_j \sim N(0, \sigma_b) \quad ; \quad g(\mu) = S \cdot BetaCDF(\mu; \lambda_1, \lambda_2)$$

Examples of $g(\mu)$ – Spillover Function

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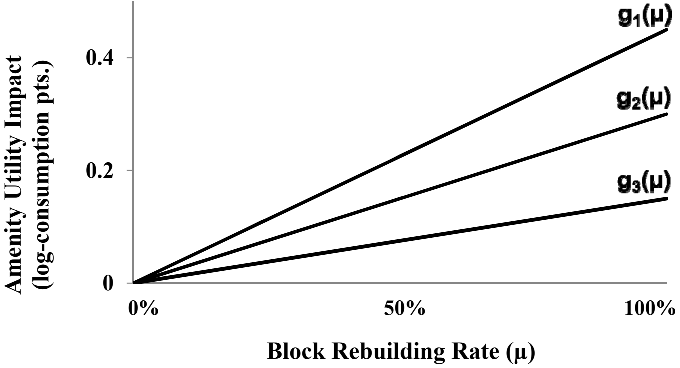

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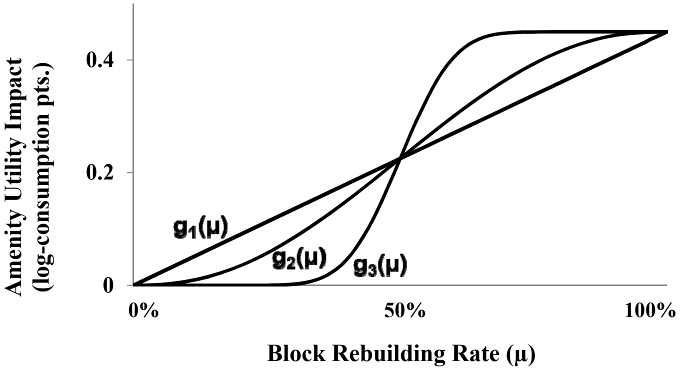

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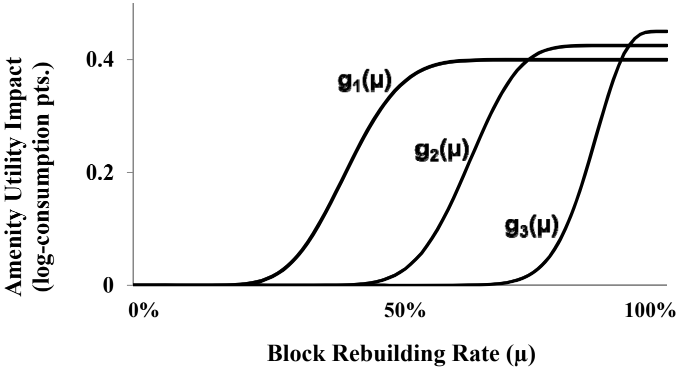

$$g(\mu) = S \cdot BetaCDF(\mu; \lambda_1, \lambda_2)$$

Model: Budget Constraint

Intertemporal Budget Constraint:

$$\begin{aligned} c_{it} \quad = \quad & \text{Location Wages}\,(d_{it}) \\ & - \text{Flow Housing Costs}\,(d_{it}) \\ & - \text{Rebuilding Costs}\,(d_{it}) \\ & + \text{Home Sale Proceeds}\,(d_{it}, \mu_{j(i),T}) \\ & + \text{Road Home Grants}\,(d_{it}) \\ & - \Delta\text{Assets}_{it} \end{aligned}$$

Borrowing constraint:

$$CreditScore_i \sim N(CreditScore_{j(i)}, 85)$$

$$\textit{Assets}_{it} \quad \geq \quad \begin{cases} -\infty & \text{if } CreditScore_i \geq \rho^* \\ 0 & \text{if } CreditScore_i < \rho^* \end{cases}$$

Model: Equilibrium

- Households' choices are best responses
- Baseline: select the "highest" equilibrium if multiple equilibria exist
- Policy experiments robust to using "opposite" eqm. selection rule

Indirect Inference Estimation

Indirect Inference Estimation

- Inner loop
    1. Draw S replications of each block
    2. Find the self-consistent period T rebuilding rates on each block
    3. Select equilibrium and store associated house prices offers
    4. For (T-1),..,2,1 find all self-consistent rebuilding rates and select eqm.

- Outer loop
    1. Compute auxiliary models $\overline{\beta}$ from data
    2. In model-simulated data, compute $\widehat{\beta}(\theta)$
    3. Solve for,

$$\widehat{\theta} = \text{argmin}_{\theta} \; [\widehat{\beta}(\theta) - \overline{\beta}]' W [\widehat{\beta}(\theta) - \overline{\beta}]$$

Choice of Auxiliary Models

1. Private rebuilding choice RD coefficients
2. Neighbors' rebuilding rate RD coefficients (avg. and "CDFs")
3. Rebuilding rates (years 1, 2,...,5) by flooding/credit-score categories

Structural Estimates: Amenity Spillover Function

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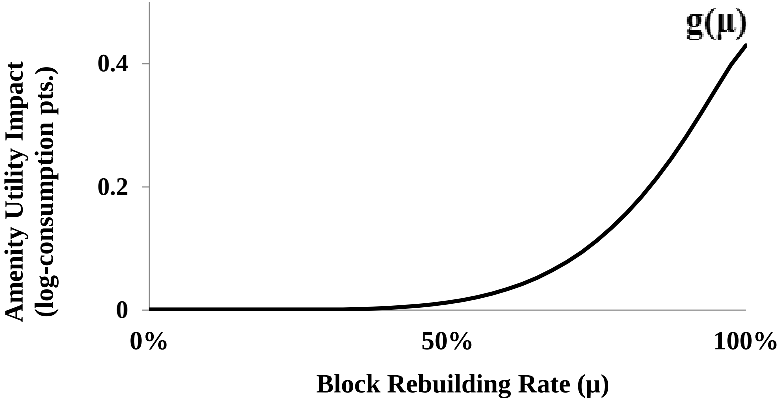
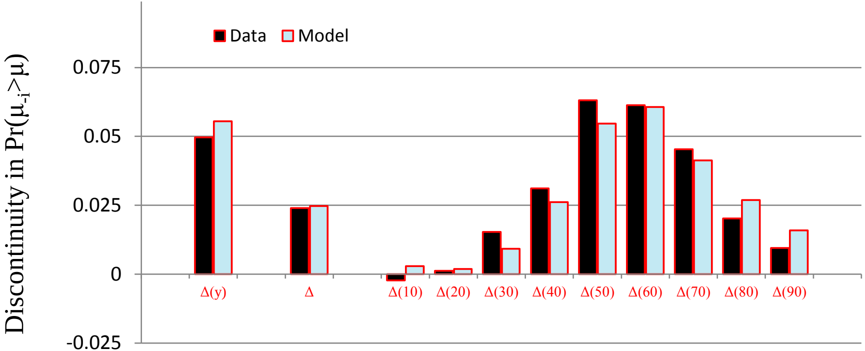


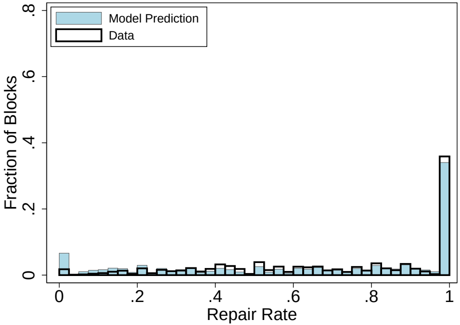
House Price Spillovers
Return

Model Fit

Model Fit – Targeted Auxiliary Models



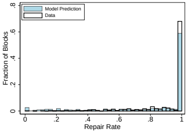
Model Fit



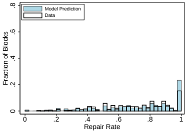
[All Blocks]

Model Fit by Flood Depth

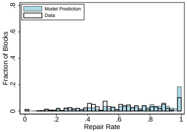
[< 2 ft.]



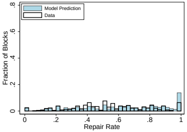
[2-3 ft.]



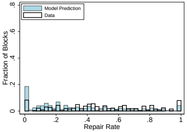
[3-4 ft.]



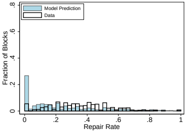
[4-5 ft.]



[5-6 ft.]

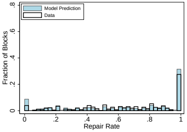


[6+ ft.]

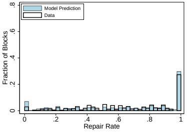


Model Fit by Average Credit Score

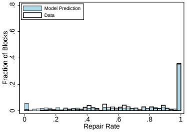
[<600]



[600-625]



[625-650]



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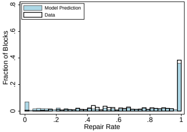
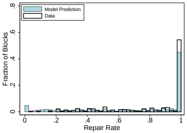


[675-700]



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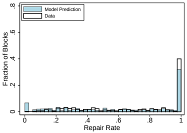

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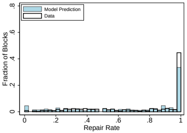


Policy Experiments

Policy Experiments

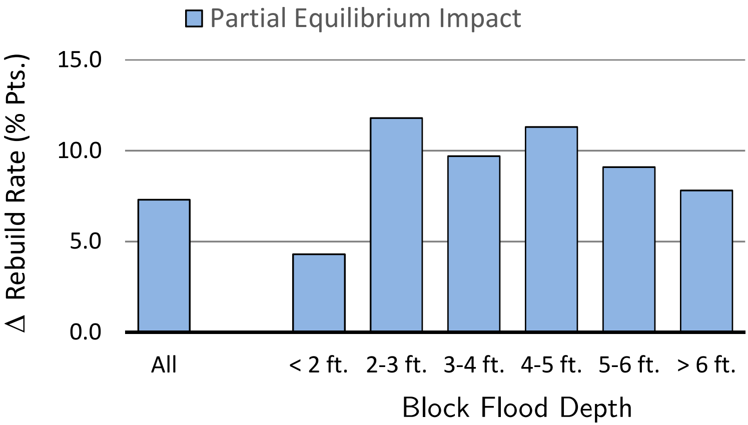
1. Road Home's equilibrium impact
   - Partial equilibrium vs. equilibrium rebuilding rate impacts

2. Welfare gain/loss from RH's conditional structure:
   - Private excess burden
   - Value of positive externality

3. Welfare improvements from targeting
   - Set (Relocation Grant) $= (1-\rho)\times$(Rebuilding Grant)
   - Find welfare-maximizing ρ^*

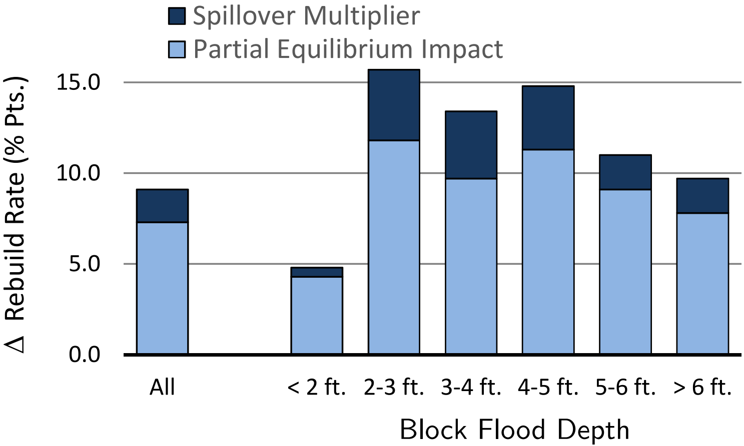
Road Home's Impact on Rebuilding

Road Home's Impact on Rebuilding (Partial Equilibrium)



Base rebuilding rate: 60%

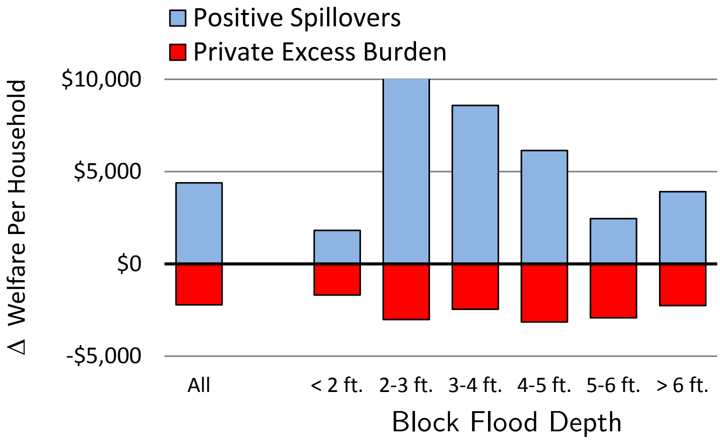
Road Home's Impact on Rebuilding



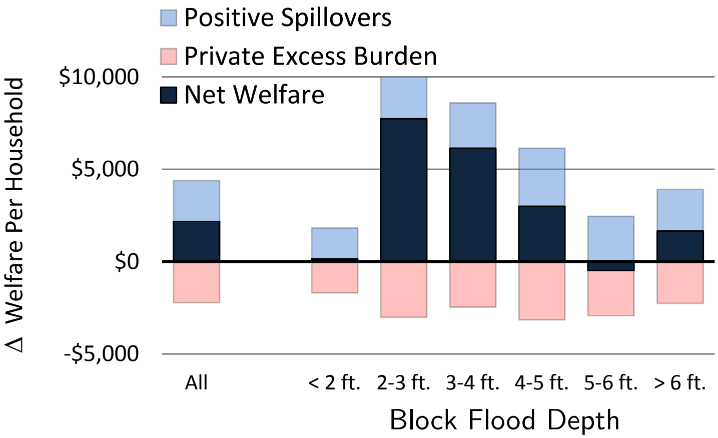
Base rebuilding rate: 60%

Road Home's Impact on Welfare

Road Home's Impact on Welfare



Road Home's Impact on Welfare



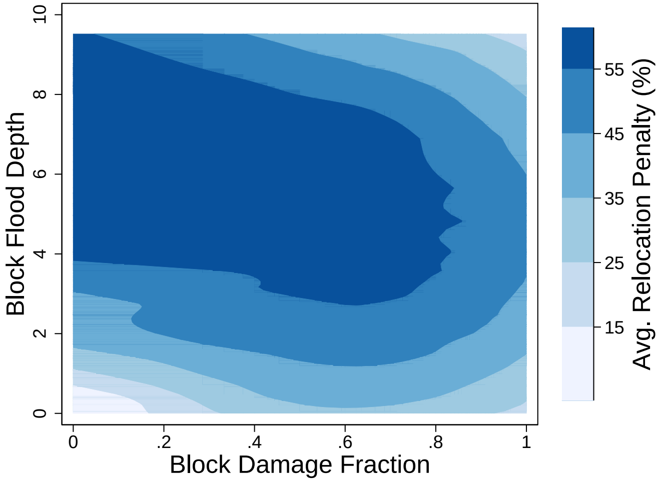
Computing Optimal Relocation Penalty

Optimal Relocation Penalties

- Class of policies:
  - Rebuild $\longrightarrow$ RH grant
  - Relocate $\longrightarrow$ RH grant$\times(1-\rho)$
- Find welfare-maximizing ρ when:
  - ρ must be uniform
  - ρ must be uniform within categories of neighborhoods

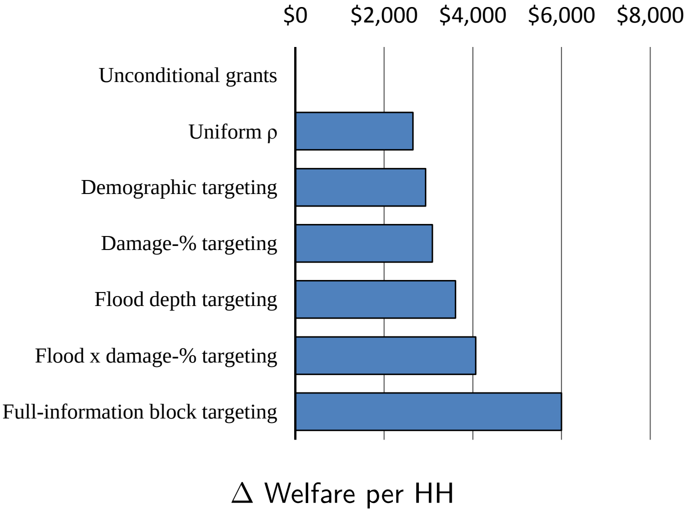
Summary of Optimal Block-Level Targeting Policy

Summary of Optimal Block-Level Targeting Policy



Targeted Relocation Penalties: Welfare Impacts

Targeted Relocation Penalties: Welfare Impacts



Conclusion

- Developed framework to estimate causal *behavioral* spillovers
- Add structure to facilitate policy experiments and welfare analysis
- Find economically important amenity spillovers
- Road Home's effective relocation penalty was welfare improving, but better targeted relocation penalties could improved welfare

Cognitive Hubs and Spatial Redistribution: Inside the Quantitative-Spatial Model

City CNR share associated with higher CNR wages

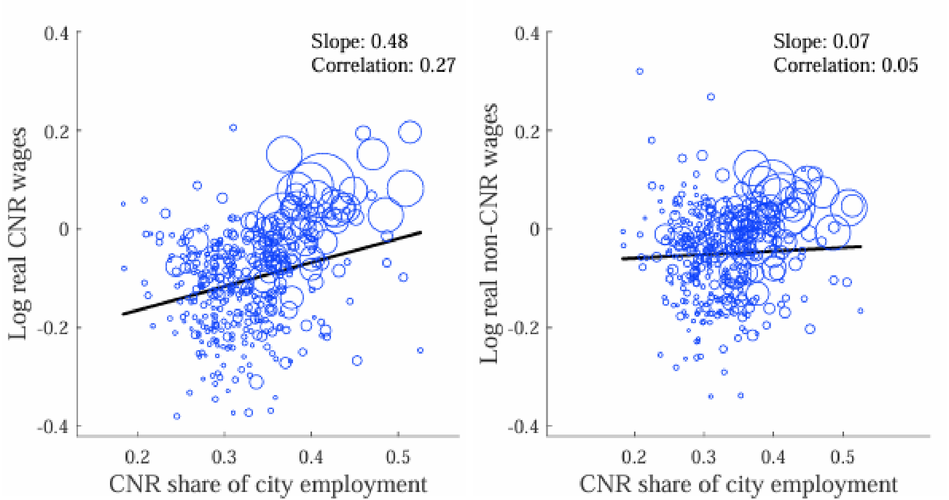


Figure 2: Occupational employment share and real wages

City CNR share causes with higher CNR-vs.-non-CNR wage premium

Figure 1: Occupational employment share and wage premium

City CNR share associated with higher CNR wages

Table 7: Instrumental Variables Estimate

	(1)		(2)		(3)	
	OLS		**2SLS**		**CUE**	
VARIABLES	CNR	non-CNR	CNR	non-CNR	CNR	non-CNR
$\gamma_n^j log(\frac{L_n^k}{L_n})$	0.889***	0.702***	1.177***	0.263	1.304***	0.835*
	(0.12)	(0.22)	(0.38)	(0.51)	(0.38)	(0.51)
$\gamma_n^j log(L_n)$	0.386***	0.322***	0.334***	0.284***	0.349***	0.357***
	(0.05)	(0.04)	(0.06)	(0.05)	(0.06)	(0.04)
Observations	7,460	7,460	7,460	7,460	7,460	7,460
K.P. F			3.912	5.425	3.912	5.425
S.W.F. L_n^k Share			5.975	8.369	5.975	8.369
S.W.F. L_n			5.997	8.587	5.997	8.587

Regressions estimates equation (10). Dependent variable is $\ln T_n^{kj}$ obtained from model inversion procedure described in text. Standard errors in parentheses, clustered two-ways by city and by industry.
*** p<0.01, ** p<0.05, * p<0.1

Research Question & Stylized Facts

- Why do **cognitive-non-routine (CNR)** jobs cluster in large cities?
- How large are the resulting **externalities**, and should a planner encourage *more* or *less* concentration?
- Data: U.S. metro areas, 1990-2015; OES employment, BEA wages, ACS rents.

Model Overview

- Workers $o \in \{c, n\}$ choose one of N cities.
- Firms produce industry goods with labor only: $Y_{ioj} = A_{ioj} L_{ioj}$.
- Iceberg trade costs and Eaton–Kortum technology draw generate *city-specific price indices*; see next slides.
- Wages equal marginal products; rents clear a housing-supply curve; migration follows a multinomial logit.

Agglomeration & Composition Externalities

Firms produce industry goods with labor only: $Y_{ioj} = A_{ioj} L_{ioj}$.

$$\ln A_{io} = a_{io} + \phi_o \ln L_i + \theta_o s_i, \qquad s_i = \frac{L_{ic}}{L_i}$$

- ϕ_o – elasticity w.r.t. overall city size.
- θ_o – productivity boost from CNR share; $\theta_c > 0$, $\theta_n \approx 0$.
- ϕ_o, θ_o are **causal IV estimates**; a_{io} recovered by inversion.

Trade Block (Eaton–Kortum within the U.S.)

- Each industry j draws productivity $A_{ioj}(z) \sim$ Fréchet(T_{ioj}, θ).
- Iceberg trade cost for good z from city i to n: $\tau_{ni}^{j} = d_{ni}^{t_j}$, d_{ni} = great-circle distance.
- **Gravity for trade shares**

$$\pi_{ni}^{j} = \frac{T_{ioj}\left(w_{ij}\tau_{ni}^{j}\right)^{-\theta}}{\sum_k T_{koj}\left(w_{kj}\tau_{nk}^{j}\right)^{-\theta}}$$

- **City-industry price index**

$$P_n^j = \left[\sum_i T_{ioj}\left(w_{ij}\tau_{ni}^{j}\right)^{-\theta}\right]^{-1/\theta}$$

Why Trade Matters for the Planner

- Price index P_n^j enters *indirectly* in real income:

$$U_{io} = \frac{w_{io}}{P_i \, R_i^{\alpha}} \exp\{\eta_i + \varepsilon_{io}\}.$$

- Clustering CNR workers raises local productivity *but* can increase P_i via congestion of goods markets.
- Trade costs therefore shape the optimal spatial pattern:
  - Low $\tau \Rightarrow$ hubs can serve the nation cheaply.
  - High $\tau \Rightarrow$ planner favors a more dispersed layout to avoid price dispersion.

Worker Utility & Migration Choice

$$U_{io} = \frac{w_{io}}{P_i\, R_i^{\alpha}} \exp\{\varepsilon_{io} + \eta_i\}, \qquad \varepsilon_{io} \sim \text{i.i.d. Gumbel}$$

- Housing share α calibrated (0.30); P_i from trade block.
- Logit migration gives:

$$L_{io} = L_o \frac{\exp\big[a_{io} + \phi_o \ln L_i + \theta_o s_i - \alpha \ln R_i - \ln P_i + \eta_i\big]}{\sum_{i'} \exp\big[a_{i'o} + \phi_o \ln L_{i'} + \theta_o s_{i'} - \alpha \ln R_{i'} - \ln P_{i'} + \eta_{i'}\big]}.$$

- Inversion recovers η_i so baseline fits observed L_{io} exactly.

Housing Supply

$$R_i = \frac{1}{\kappa_i} L_i^{\gamma}, \qquad \gamma \text{ calibrated from rent–size elasticity}$$

- κ_i inverted city-by-city.
- Rising R_i dampens migration toward large hubs.

Equilibrium Algorithm (Counterfactuals)

1. Start with baseline L_{io}.
2. **Update wages**: $w_{io} \leftarrow \exp[a_{io} + \phi_o \ln L_i + \theta_o s_i]$.
3. **Update prices** P_i via EK gravity using new wages.
4. **Update rents** R_i from housing supply.
5. **Update migration** L_{io} via gravity utility.
6. Repeat steps 2–5 until convergence (sec.-level runtime).

Planner's Objective with Pareto Weights

$$\max_{\{L_{io}\}} \sum_i \sum_o \omega_o \, L_{io} \left[\ln w_{io} - \ln P_i - \alpha \ln R_i + \eta_i\right]$$

- ω_o = *Pareto weight* on occupation o.
- Baseline paper sets $\omega_c = \omega_n = 1$ (utilitarian).
- Researcher can tilt policy toward low-skill workers by raising ω_n/ω_c:
  - Higher weight transfers redistribute more to non-CNR.
  - Spatial pattern shifts: low-skill hubs grow; high-skill hubs shrink.
- Same fixed-point solver applies after adding the ω_o weights.

Key Estimates & Externality Evidence

- Social value of a CNR worker $= 1.79\times$ private value.
- Size elasticity similar across groups; CNR-share elasticity large only for CNR.

Optimal Policy: "Cognitive Hubs"

- With $\omega_c = \omega_n = 1$:
  - CNR workers concentrate further in large cities.
  - Non-CNR workers move to smaller cities; transfers $\approx$ \$16.9k to each non-CNR, –\$15.3k from each CNR.
- Raising ω_n/ω_c dampens CNR concentration and flattens transfers.

Conclusions

- Papers often read as if researcher started with a question, found appropriate IV
  - Sometimes that works, but IVs / natural experiments are hard to find
  - Particularly in Urban
- Often research process goes the other way:
  - See a natural experiment, policy quirk, etc.
  - Ask what narrow causal effect the experiment credibly identifies
  - Ask what important economic/policy question that LATE is related to
  - Is there a credible way, potentially using a model, to extrapolate from the LATE?
- Suggestion: stay open to both top-down and bottom up approaches