Public Economics (2450B)

Topic 6: Place-Based Policy

Nathaniel Hendren*

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Place–Based Policy

Many policies are implemented at the local level

- Taxes (Property, sales, and corporate)
- Spending (Education, Health, UI, …)
- Regulations (e.g. zoning)

Many national policies have local implications (e.g. Section 8 / Housing Choice Vouchers, LIHTC, etc.)

How should layers of government be organized? How should local and fed govt interact? These are questions about "Fiscal Federalism":

- Should the federal government or local government set property taxes?
- Who should pay for schools?
- Should local or federal governments redistribute?

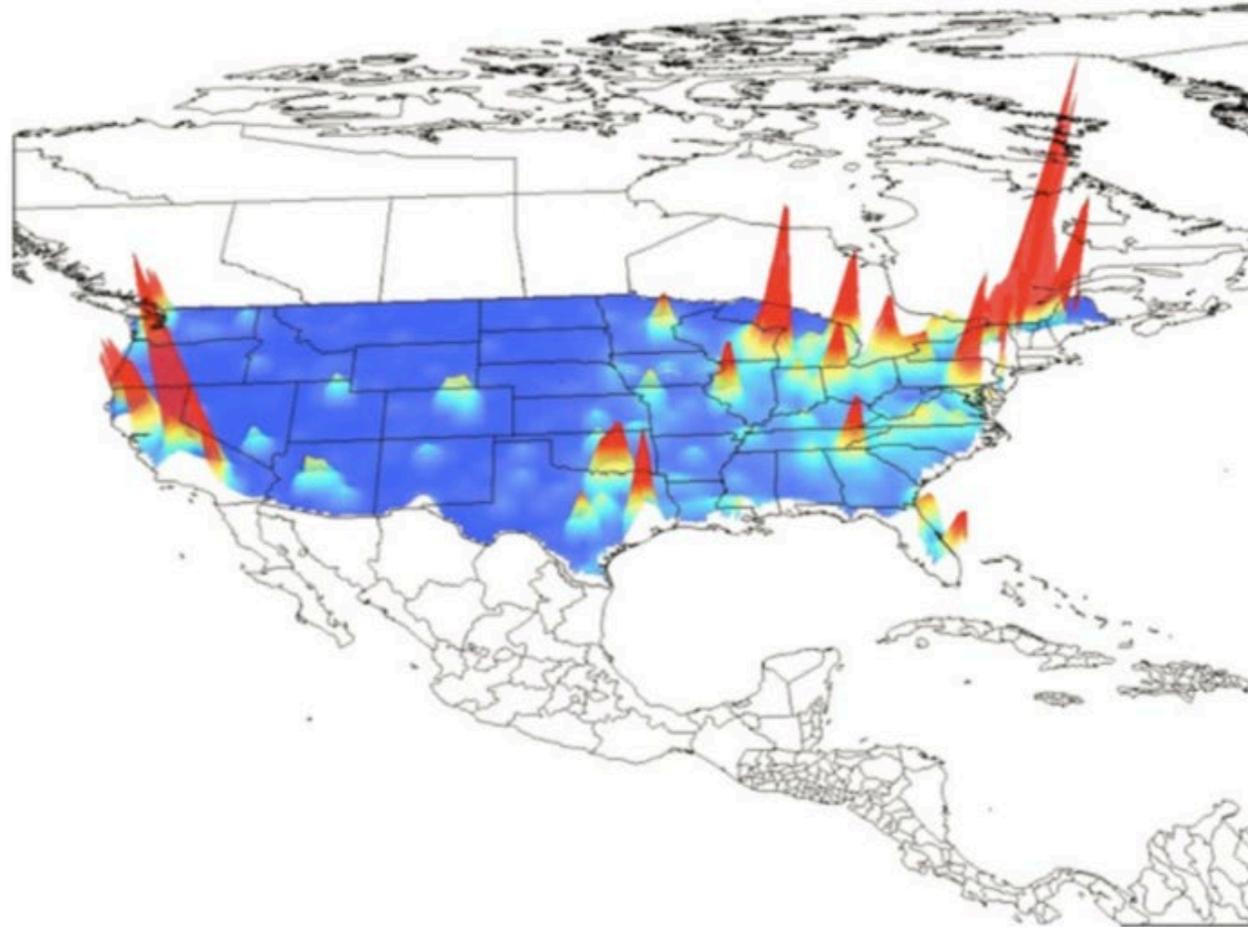# Economic Activity is Geographically Concentrated ([Moretti 2011](#))
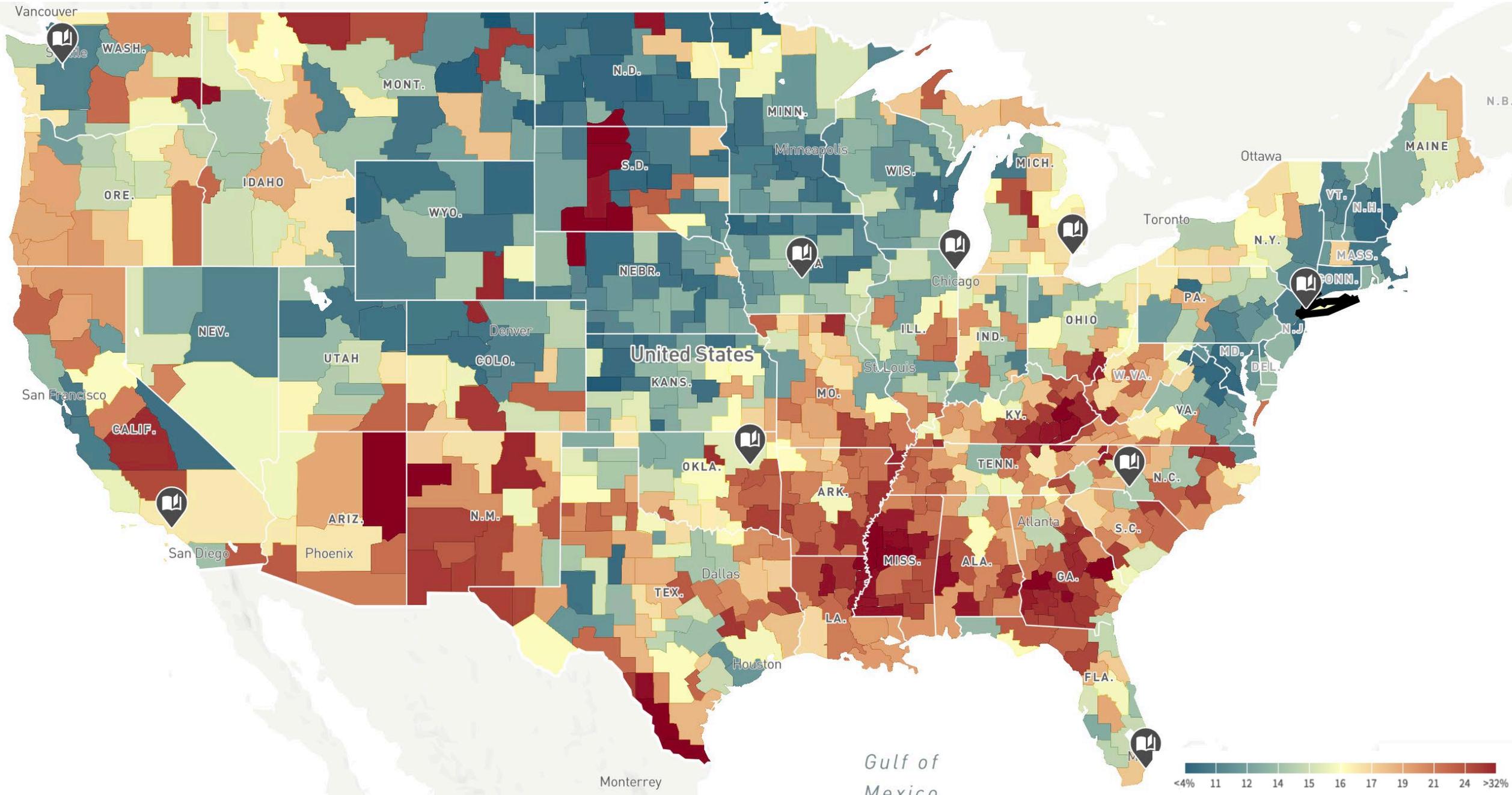

Figure 1 *Spatial distribution of economic output in the US, by square mile.* Notes: This figure reports the value of output produced in the US by square mile.

Source: Moretti (2011)

Poverty is Geographically Concentrated (2012-2016 Poverty Rates from ACS)

Legend: <4% 11 12 14 15 16 17 19 21 24 >32%

Exposure to Trade Competition from China is Geographically Concentrated

Most-affected areas of the U.S.

Colors show which areas were most affected by China's rise, based on the increase in Chinese imports per worker in each area from 1990 to 2007. Hovering over each area on the map will show a demographic breakdown of that area, below, and its most-affected industries, at right.

Most-affected 20%   Second-highest 20%   Middle 20%   Second-lowest 20%   Least-affected 20%
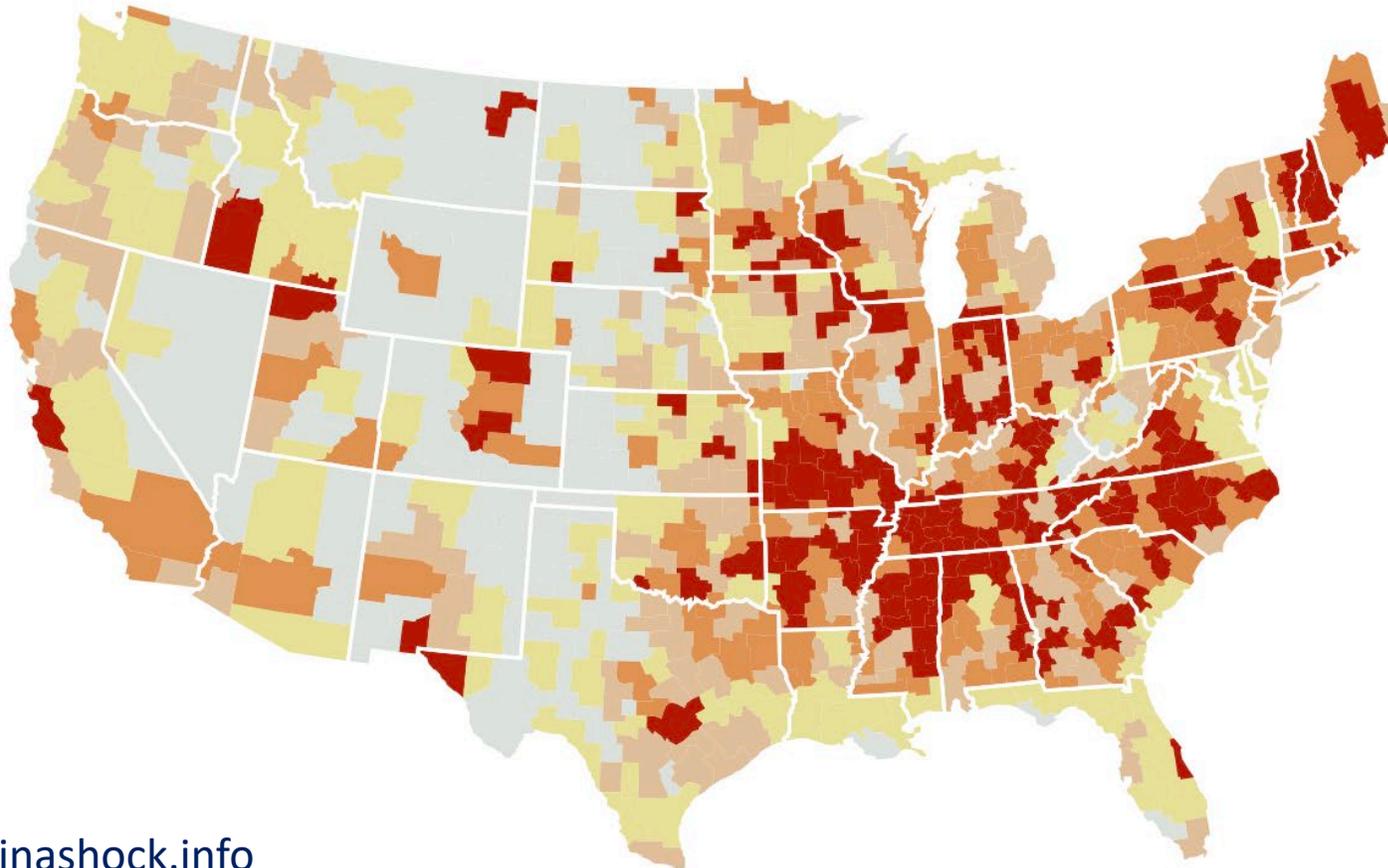
Most-affected industries

Most-affected industries, based on number of areas*

Impact per worker†

Furniture and fixtures
196 areas $44k

Games, toys, and children's vehicles
114 areas $488k

Sporting and athletic goods
106 areas $82k

Electronic components
87 areas $65k

Plastics products
84 areas $11k

Motor-vehicle parts and accessories
79 areas $12k

Electronic computers
68 areas $207k

Source: chinashock.info

Recovery from Recession varies by Geography ([Yagan 2019 JPE](#))

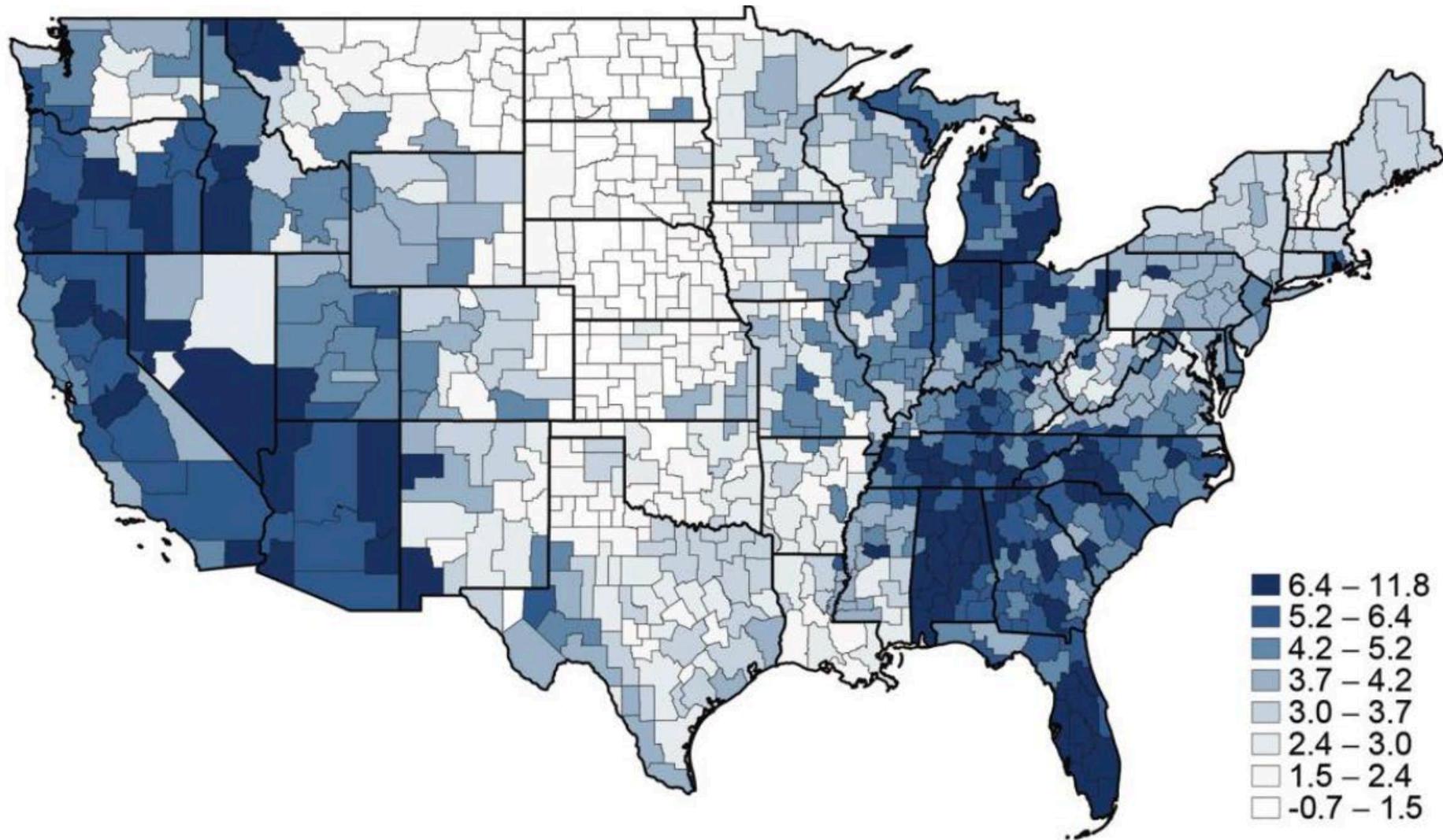|	
■	6.4 – 11.8
■	5.2 – 6.4
■	4.2 – 5.2
■	3.7 – 4.2
■	3.0 – 3.7
□	2.4 – 3.0
□	1.5 – 2.4
□	-0.7 – 1.5

FIG. 3.—Great Recession local shocks. This map depicts unweighted octiles (divisions by increments of 12.5 percentiles) of Great Recession local shocks across commuting zones (CZs). CZs span the entire United States and are collections of counties that share strong commuting ties. Each CZ's shock equals the CZ's 2009 LAUS unemployment rate minus the CZ's 2007 LAUS unemployment rate. In the individual-level analysis, I assign each individual to the Great Recession local shock of the individual's January 2007 CZ.

UI Expansion During the Recession Responded Heterogeneously
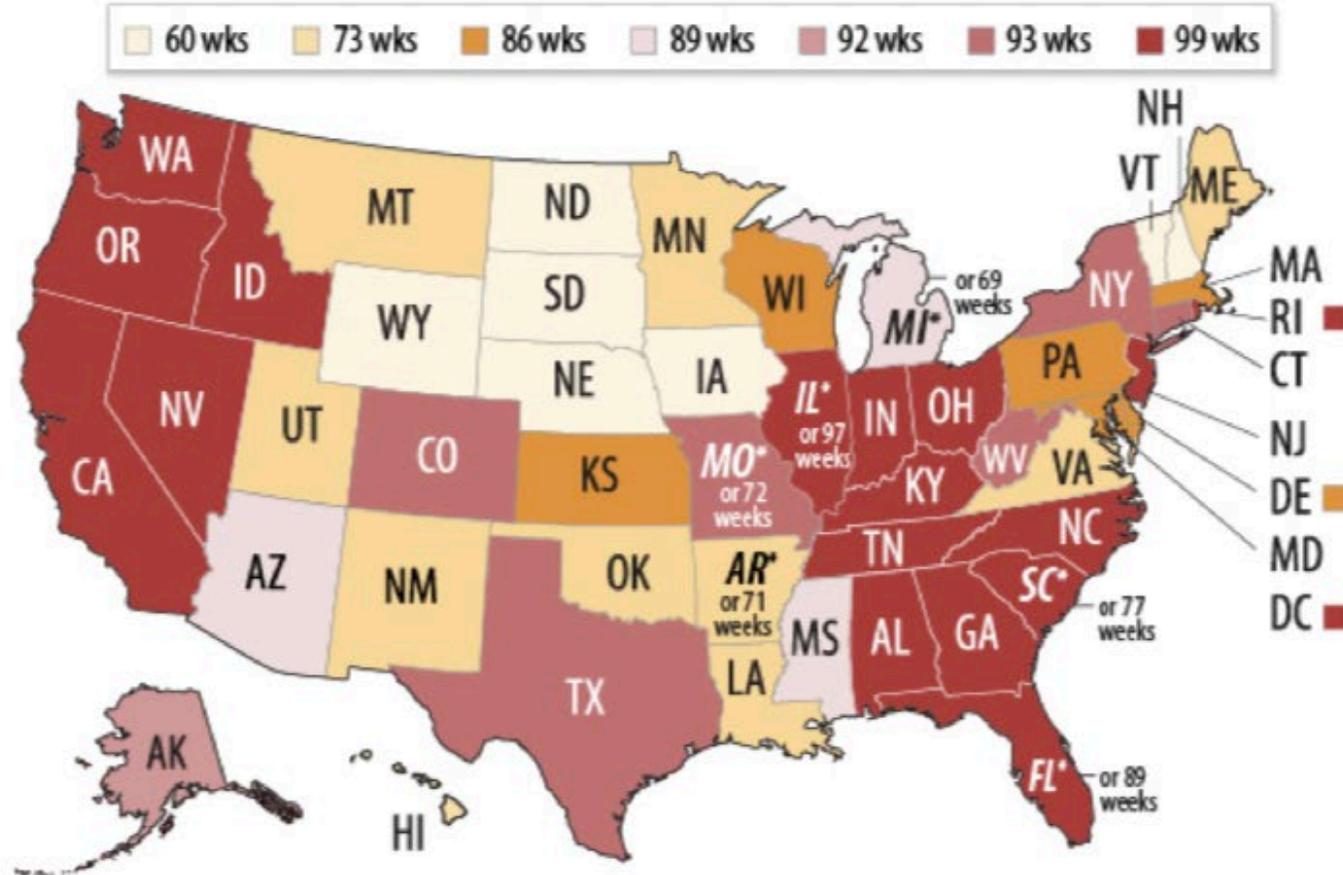
Source: CBPP (2012)

Life Expectancy varies by Geography ([Chetty et al. (2016)](#))

Geography of Life Expectancy in the Bottom Income Quartile

Life Expectancy at Age 40 (race-adjusted)
- >80.7
- >80.1 – ≤80.7
- >79.7 – ≤80.1
- >79.4 – ≤79.7
- >79.1 – ≤79.4
- >78.9 – ≤79.1
- >78.6 – ≤78.9
- >78.3 – ≤78.6
- >77.9 – ≤78.3
- ≤77.9
- Insufficient Data
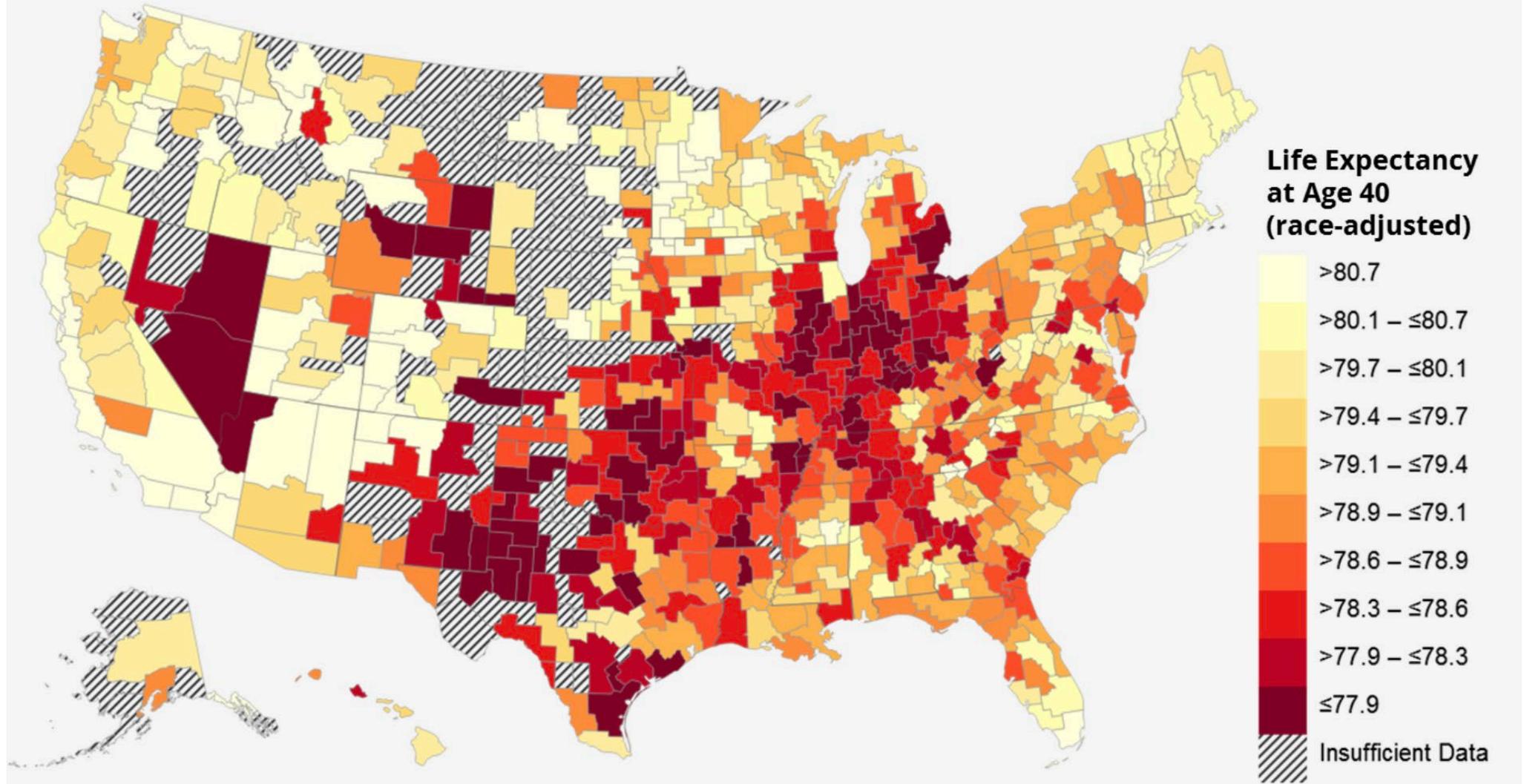
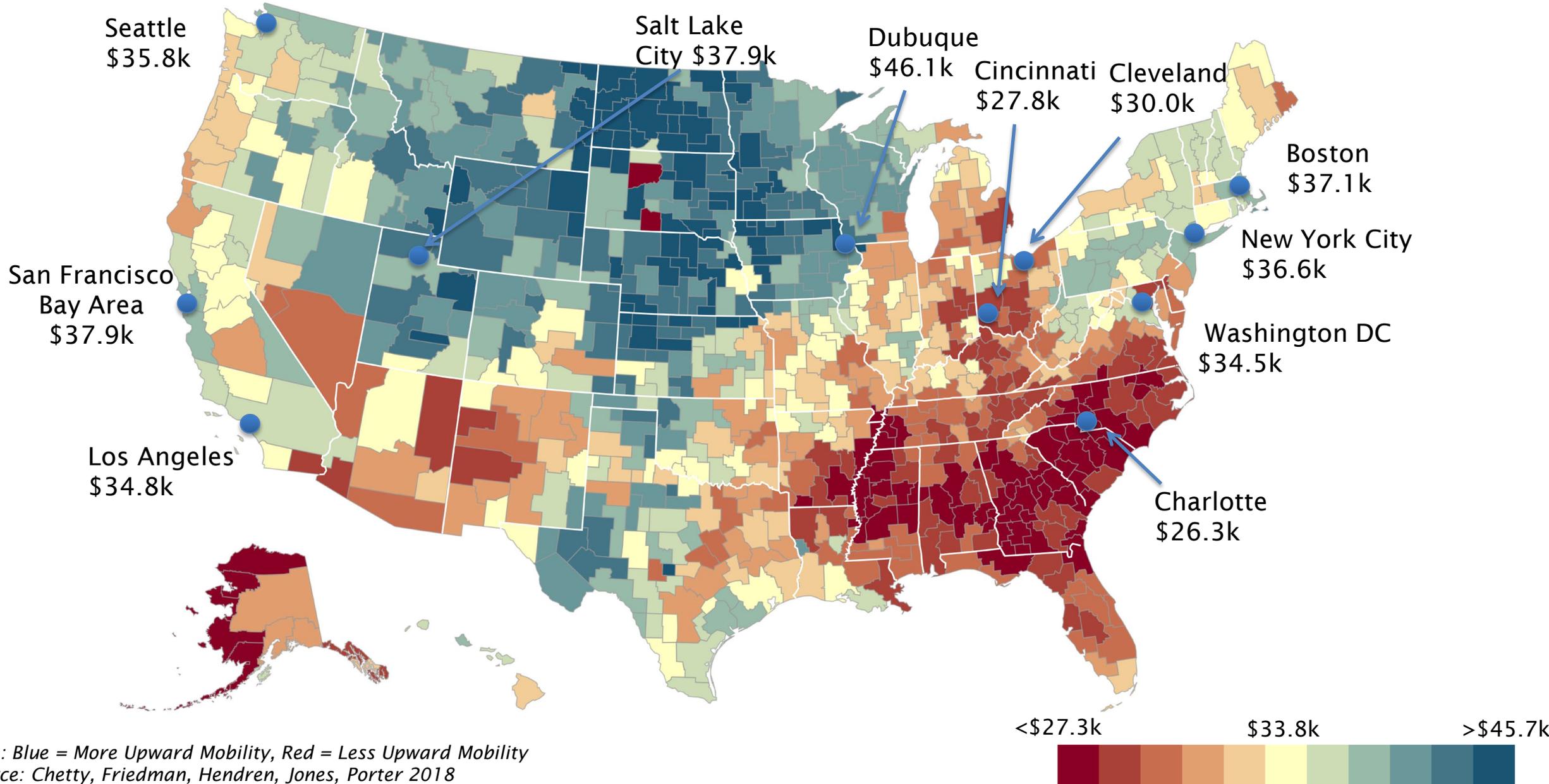Top 5 Cities: New York City NY, Santa Barbara CA, San Jose CA, Miami FL, Los Angeles CA

Bottom 5 Cities: Tulsa OK, Indianapolis IN, Oklahoma City OK, Las Vegas NV, Gary IN

Source: Heathinequality.org

ACA Medicaid Expansions Varied Across States

Status of State Action on the Medicaid Expansion Decision

Legend:
- **Adopted and Implemented** (dark blue)
- **Adopted but Not Implemented** (blue)
- **Not Adopted** (orange)

Upward Mobility Varies Across the US

Average Income at Age 35 for Children whose Parents Earned $27,000 (25th percentile)

Seattle
$35.8k

Salt Lake
City $37.9k

Dubuque
$46.1k

Cincinnati
$27.8k

Cleveland
$30.0k

Boston
$37.1k

San Francisco
Bay Area
$37.9k

New York City
$36.6k

Washington DC
$34.5k

Los Angeles
$34.8k

Charlotte
$26.3k

<$27.3k $33.8k   >$45.7k

Note: Blue = More Upward Mobility, Red = Less Upward Mobility
Source: Chetty, Friedman, Hendren, Jones, Porter 2018

Education Spending Varies Across States
Per Pupil Spending by State (2020)

Amount Spent Per Pupil

< $10,000   > $10,000   > $12,000   > $14,000   > $16,000   > $18,000   > $20,000   > $22,000

US Census Data from http://worldpopulationreview.com/states/per-pupil-spending-by-state/
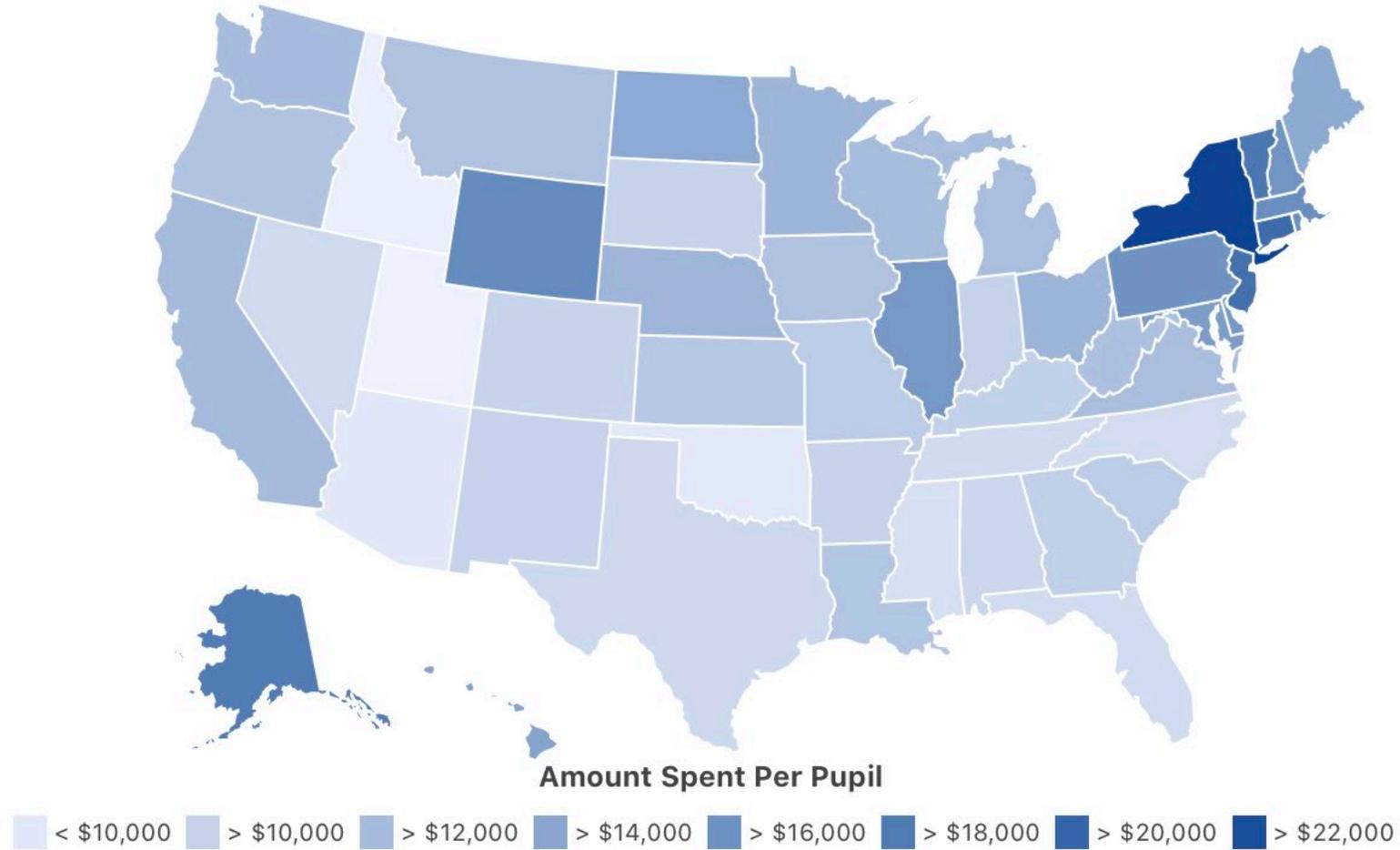
Median Rent Varies Across the US (2012-2016 ACS)
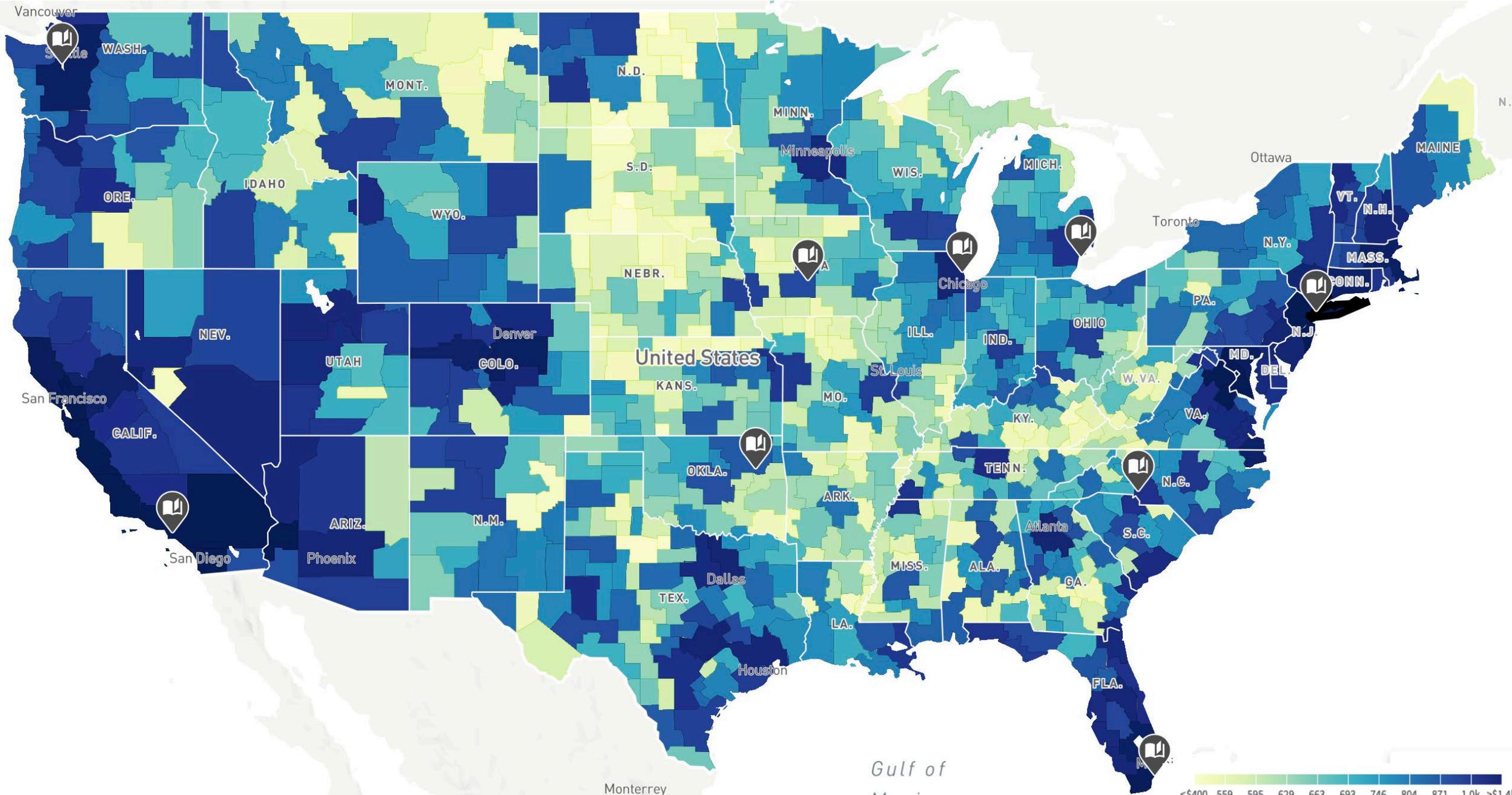
This lecture

- Develop models that think about space and use them to think about optimal policy

- Key thing we need to incorporate into models: (endogenous) price of location

- Begin with simple "Rosen Roback" model

  - Extend to case with infra-marginal residents ([Kline and Moretti 2013](#))

  - Discuss optimal policy / fiscal federalism: Oates and Tiebout

- Discuss empirical evidence on impact of place-based policies

Outline

1 **Models Spatial Sorting and Optimal Policy**

2 **Empirical Evidence on Impact of Place-Based Policies**

Rosen and Roback

- Rosen and Roback model outlines increased amenities in an area translate into incidence on land owners and workers

  - In class, I will Owen Zidar's 14.472 MIT Lectures for discussion of Rosen-Roback model and derive the pass through of changes in amenities on prices of labor and land

- Given people respond to differences in local policies, how should optimal policy respond?

- Tiebout JPE 1956 provides an answer:

Tiebout (1954)

- Local government j provides a non-rival local public good available only to those in the locality
  - Good is potentially non-rival but excludable via location (e.g. need to live in the place to benefit)
  - Individuals are perfectly mobile

- Governments cover the cost of spending through uniform, jurisdiction-based lump-sum taxes on residents

- There is a large # of jurisdictions relative to # of individuals with different preferences for gov spending so that everyone can find a place on the frontier of amenities and prices

- Result: sorting across place leads to efficient allocation of individuals

- Efficient equilibrium where everyone sorts to optimal preferred set of public goods

Oates (1972)

- Oates (1972) considers question of fiscal federalism: what levels of government should do each activity?

- Redistribution: difficult to conduct locally because people can move → tax schedule redistributes at national level

- Fiscal federalism: let spending decisions happen at a local level, but raise revenue nationally (and provide national public goods like defense)

Outline

① **Models Spatial Sorting and Optimal Policy**

② **Empirical Evidence on Impact of Place-Based Policies**

Impact of firm taxation on place location

- Focus on two classes of empirical work:

  - Firm Policies

  - Housing Policies

- Begin with Firm Policies

Direct Firm Subsidies

- Large firms often lobby for and receive subsidies from localities (e.g. tax cuts and credits)

    – e.g. Amazon competition

- Slattery and Zidar ([2020 JEP](#)) study subsidies for local firms using data on special tax deals between firms and localities

- Begin with case study of 2008 Volkswagon deal

Direct Firm Subsidies

- VW chooses Chattanooga for new assembly plant • Promises 2,000 emp and $1B investment

- TN grants VW a subsidy worth $558 million
  - Local property tax abatements over 30 years ($200M)
  - Enhanced state job and investment tax credits over 20 years ($200M) • Property given to VW ($81M)
  - Worker training ($30M)
  - Highway and road construction ($43M) + Rail line upgrades ($3.5M)

- Runner up: Huntsville, AL offers $386 million package

Direct Firm Subsidies

Employment in Transportation Equipment Manufacturing
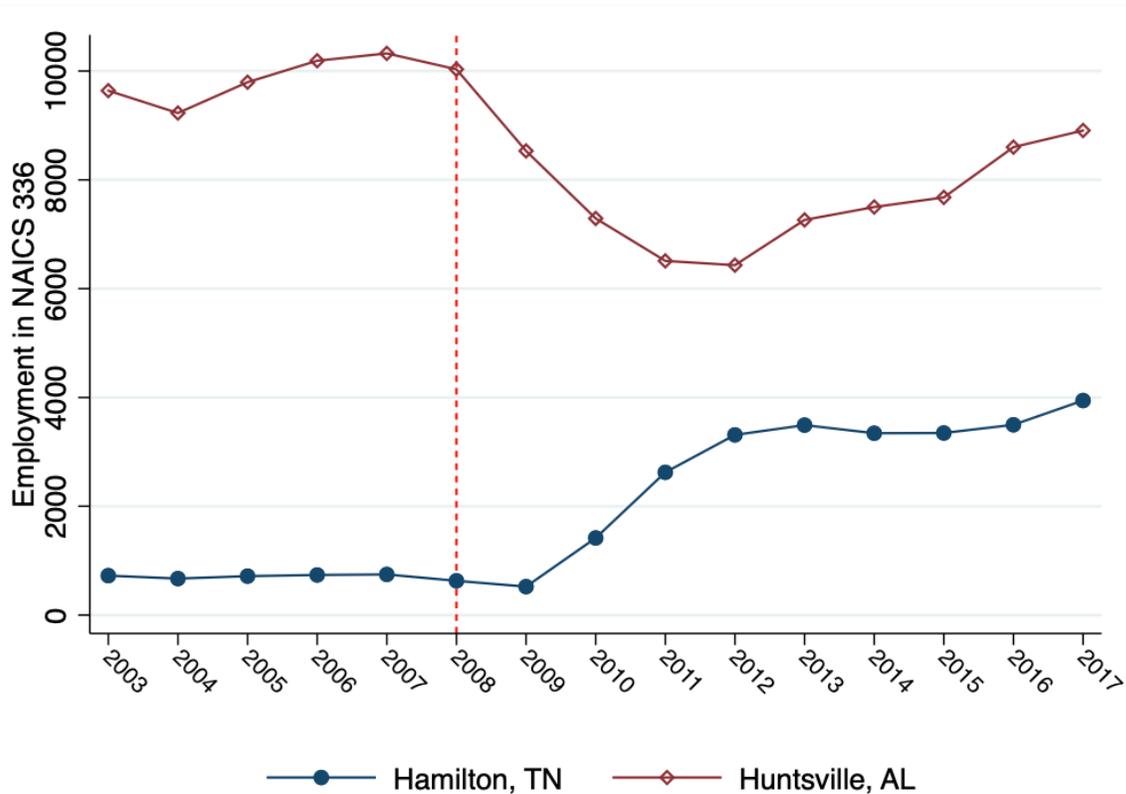
Differences in Employment Between Winner and Runner-up
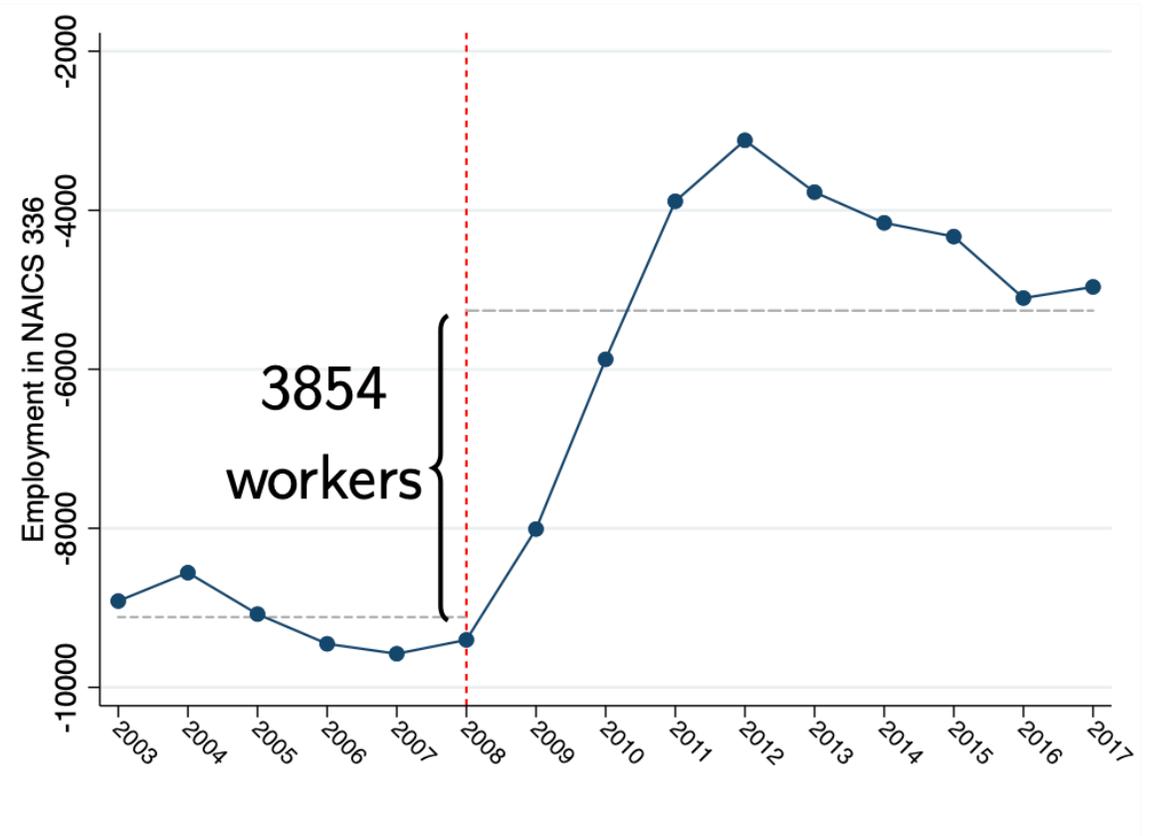
Direct Firm Subsidies

- Expand event study design to compare "winner" to "runner-up" counties for deals between 2002-2012

For every period in event time $t \in [-5, 5]$, we run the following regression

$$\ln Y_{it} = \alpha_t + \beta_t Winner_i + \mathbf{X_i}\gamma' + \delta_{dealyr} + \varepsilon_{it}$$

- $\ln Y_{it}$: log employment in the 3-D industry of the deal t periods relative to year of deal

- $Winner_i$ is an indicator for county i having won a discretionary deal, 0 for runner up

- α_t: controls for year fixed effects

- $\mathbf{X_i}$: controls for log employment, log population, and log average wages 10 years pre-deal

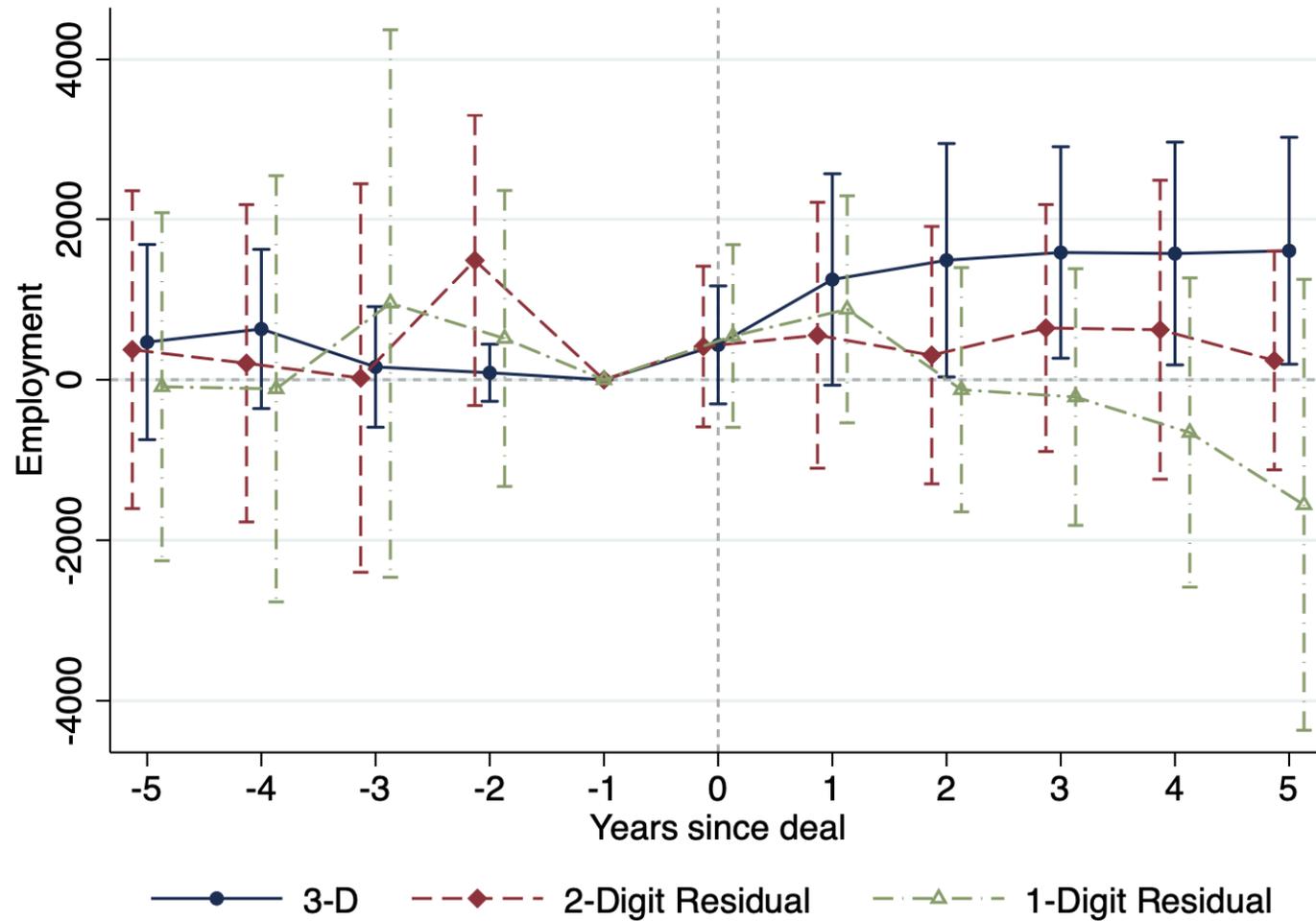- δ_{dealyr}: calendar year-of-deal fixed effects

We then plot $\beta_t - \beta_{t=-1}$ for $t \in [-5, -4, -3, -2, 0, 1, 2, 3, 4, 5]$.

Effect within Industry
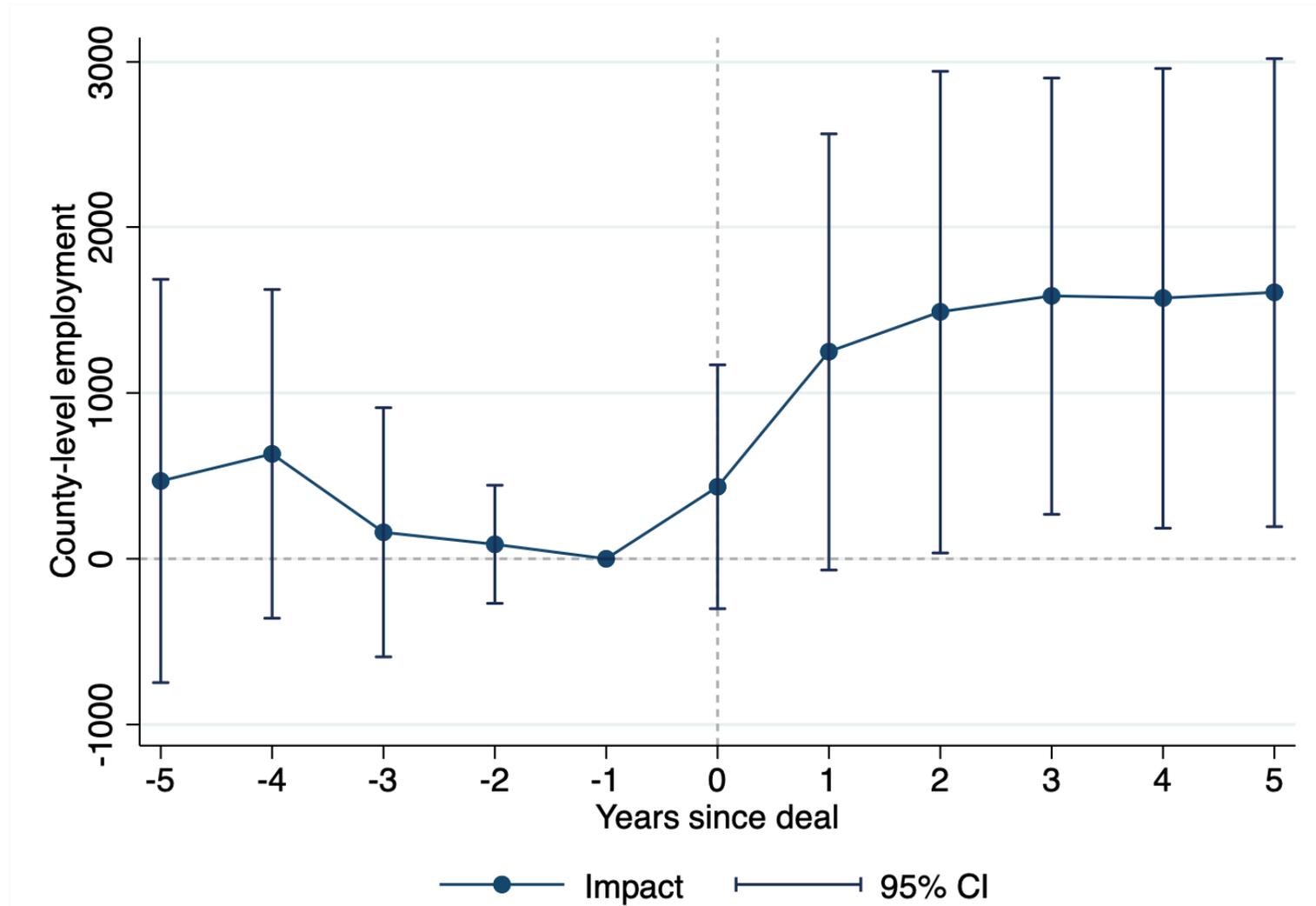
Notes: This figure shows the event study estimates of the effect of winning a firm-specific deal on county level employment within the NAICS 3-digit industry of deal

No Evidence of Spillover Effects to Other Industries

Notes: This figure shows event study estimates of the effect of winning a firm-specific deal on three outcomes: employment in 3-digit industry of deal, 2-digit residual employment, and 1-digit residual employment.

No Evidence of Spillover Effects to Other Industries

	3-D Ind. Employment (1)	Res. 2-D Ind. Employment (2)	Res. 1-D Ind. Employment (3)	Res. County-wide Employment (4)	Personal inc. (5)	log HPI (6)	Emp/pop (7)
Panel A. Levels Estimates							
Winner × Post	1108.287**	780.238	53.154	-1920.430	-1090.989	N/A	-0.001
	(539.686)	(1096.283)	(1928.740)	(5301.175)	(716.305)	N/A	(0.002)
Mean of outcome	9326.605	15763.784	49393.076	2.80e+05	49826.006	N/A	0.470
Panel B. Log Estimates							
Winner × Post	0.149**	0.026	0.030	0.003	-0.005	-0.040*	-0.002
	(0.068)	(0.027)	(0.019)	(0.013)	(0.012)	(0.021)	(0.004)
Mean of outcome	7.965	9.037	9.922	12.006	16.667	4.858	-0.759

Notes: This table shows difference-in-differences estimates of the effects of winning a firm-specific deal on a variety of county-level outcomes.
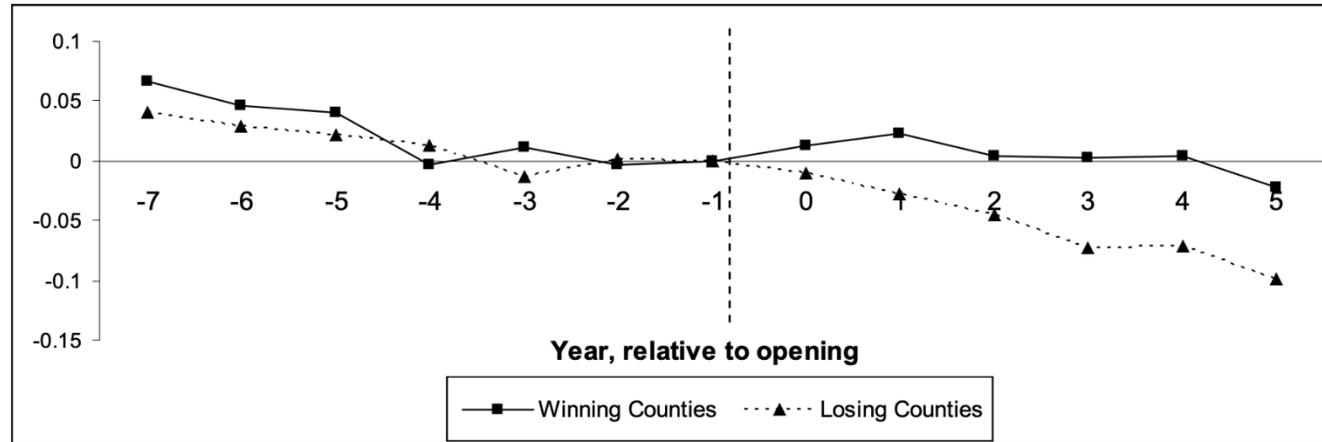
Lack of Spillovers Differs from Prior Literature

- "Million Dollar Plants" data: 82 subsidy deals from Site Selection Magazine, mostly manufacturing, in 1980s and 90s (Greenstone & Moretti 2003)

- Relies on reported location rankings of large firms' location choices

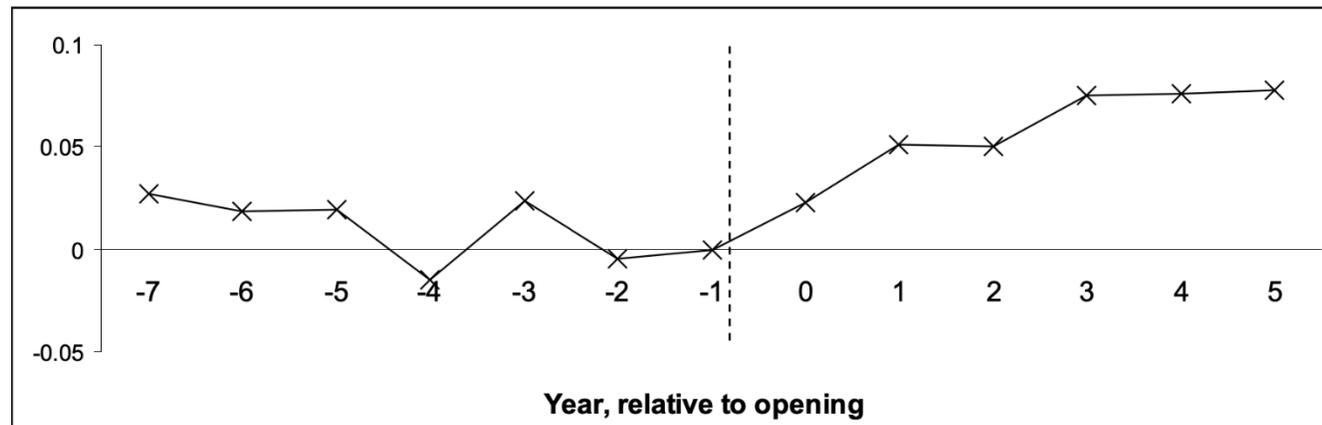- Compares top to 2nd highest ranked places

Lack of Spillovers Differs from Prior Literature

Figure 1. All Incumbent Plants' Productivity in Winning vs. Losing Counties, Relative to the Year of a MDP Opening

All Industries: Winners vs. Losers
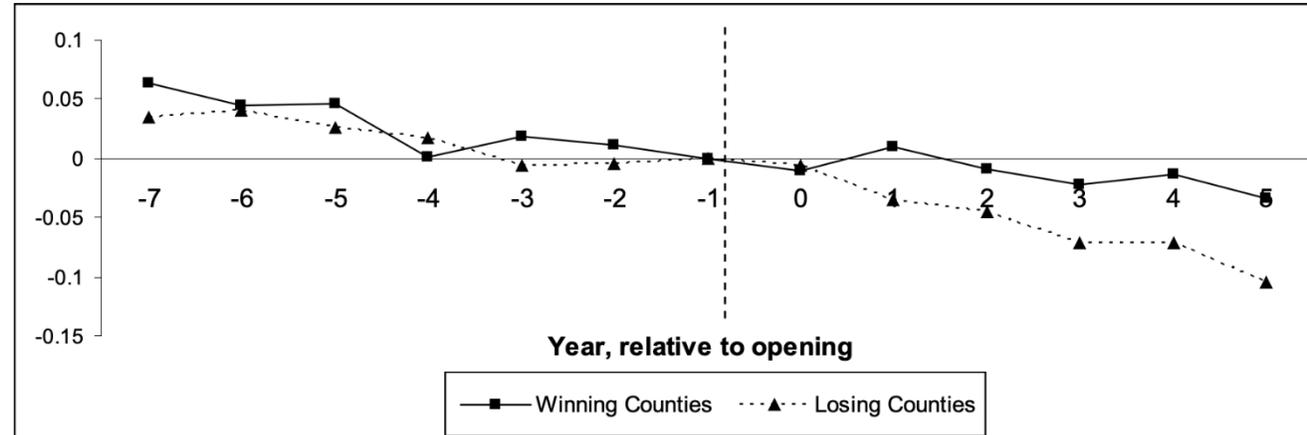

Difference: Winners – Losers

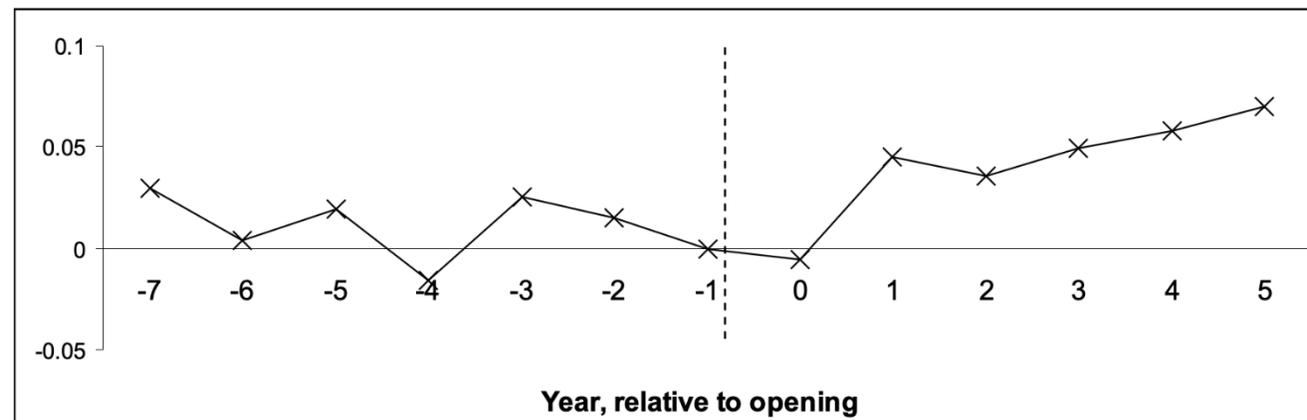Notes: These figures accompany Table 4.

Lack of Spillovers Differs from Prior Literature

Figure 4. Incumbent Plants' Productivity in Other Industries (not the MDP's 2-Digit Industry), Winning vs. Losing Counties, Relative to the Year of a MDP Opening

Notes: These figures accompany Table 7, Column 3 (All 2-digit Industries, except the MDP's 2-digit Industry).

Impact of Depreciation Generosity on Local Labor Markets

- Federal subsidies can also have heterogeneous local effects (and can help isolate potential spillover effects)

- Garnett, Ohrn, and Suarez Serrato (2019) study the impact of accelerated depreciation on local labor markets

- Study "bonus depreciation" that allows firms to deduct an additional percentage of capital expenditures in the first year of an asset's tax life.

- Bonus depreciation has larger effects where firms invest in longer-lived assets

- Measure a county's exposure to bonus depreciation by interacting industry-level heterogeneity in the benefit of bonus depreciation with industry location data

Impact of Depreciation Generosity on Local Labor Markets

- Exploit 2002 Job Creation and Worker Assistance Act

- Enacted 30% bonus depreciation, later increased to 50% in 2003-2004, then canceled in 2005 and re-implemented at 50% in response to 2008 recession for 2008-17 (aside from 100% in 2011).

- Large body of work shows increased firm investment in response to bonus depreciation
  - House and Shapiro (2008), Edgerton (2010), Cummings et al (2004)

- Transition estimates to exposure in local labor markets using shift-share design

Impact of Depreciation Generosity on Local Labor Markets

- Construct local labor market measure of exposure to bonus depreciation

- Classify industries by those with long-lived assets

- Construct fraction of local employment in 2001 that is in these industries

$$\textbf{Exposure}_c = \frac{\sum_j Emp_{jc2001}\mathbb{I}(treated_j = 1)}{\sum_j Emp_{jc2001}}$$

Impact of Depreciation Generosity on Local Labor Markets

- Run regression of employment growth in county c industry j in year t:

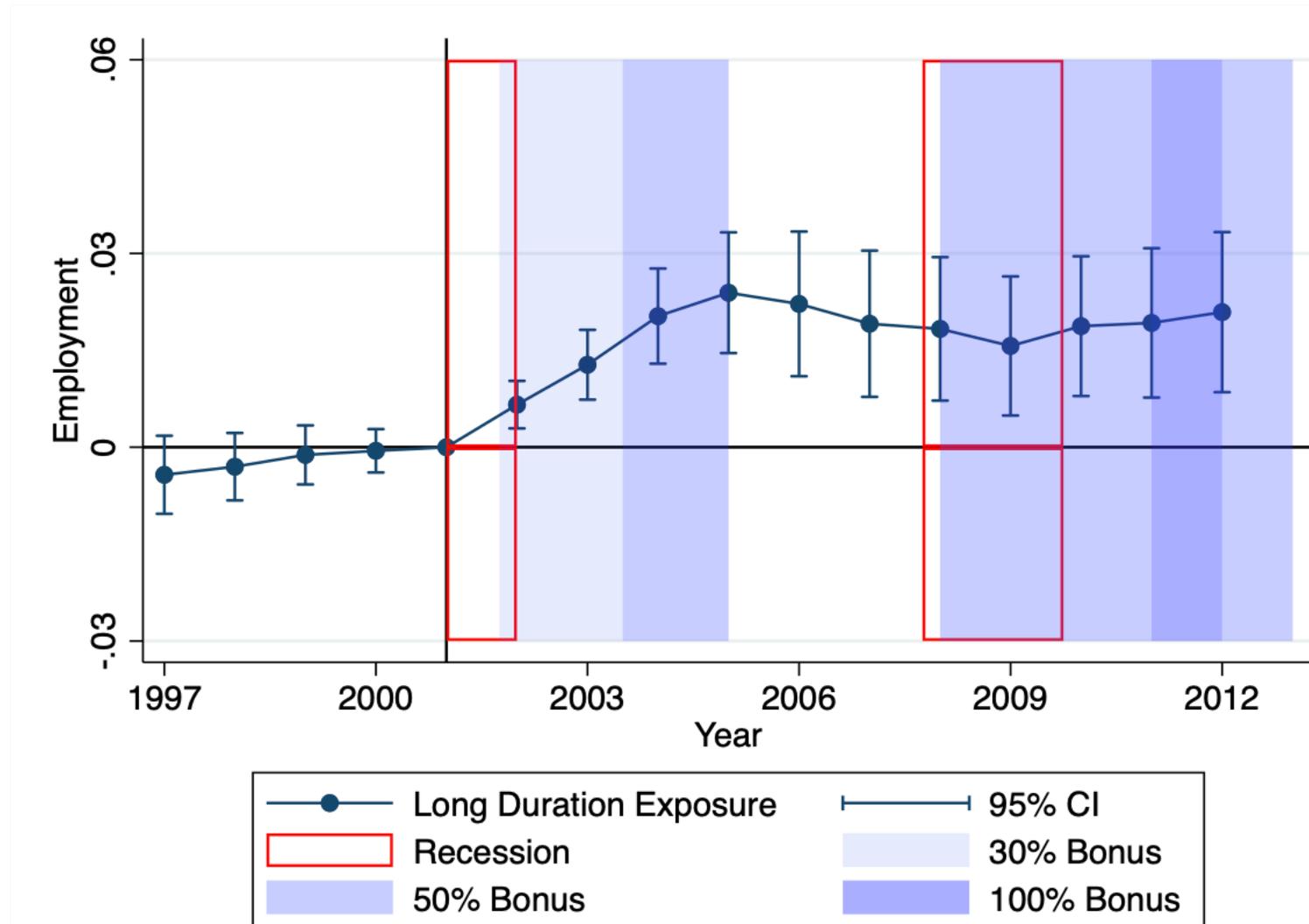$$\Delta Emp_{cjt} = \alpha + \sum_{y=1997}^{2012} \beta_y \left[\mathbf{Exposure}_c \times \mathbb{I}(t = y) \right] + \mathbf{X'}_c \boldsymbol{\gamma}_t + \mu_{st} + \nu_{jt} + \epsilon_{cjt},$$

where

$$\Delta Emp_{cjt} \equiv \frac{Emp_{cjt} - Emp_{cj2001}}{Emp_{cj2001}}$$

Impact of Depreciation Generosity on Local Labor Markets
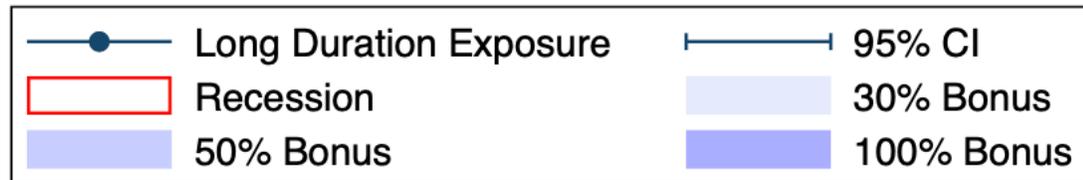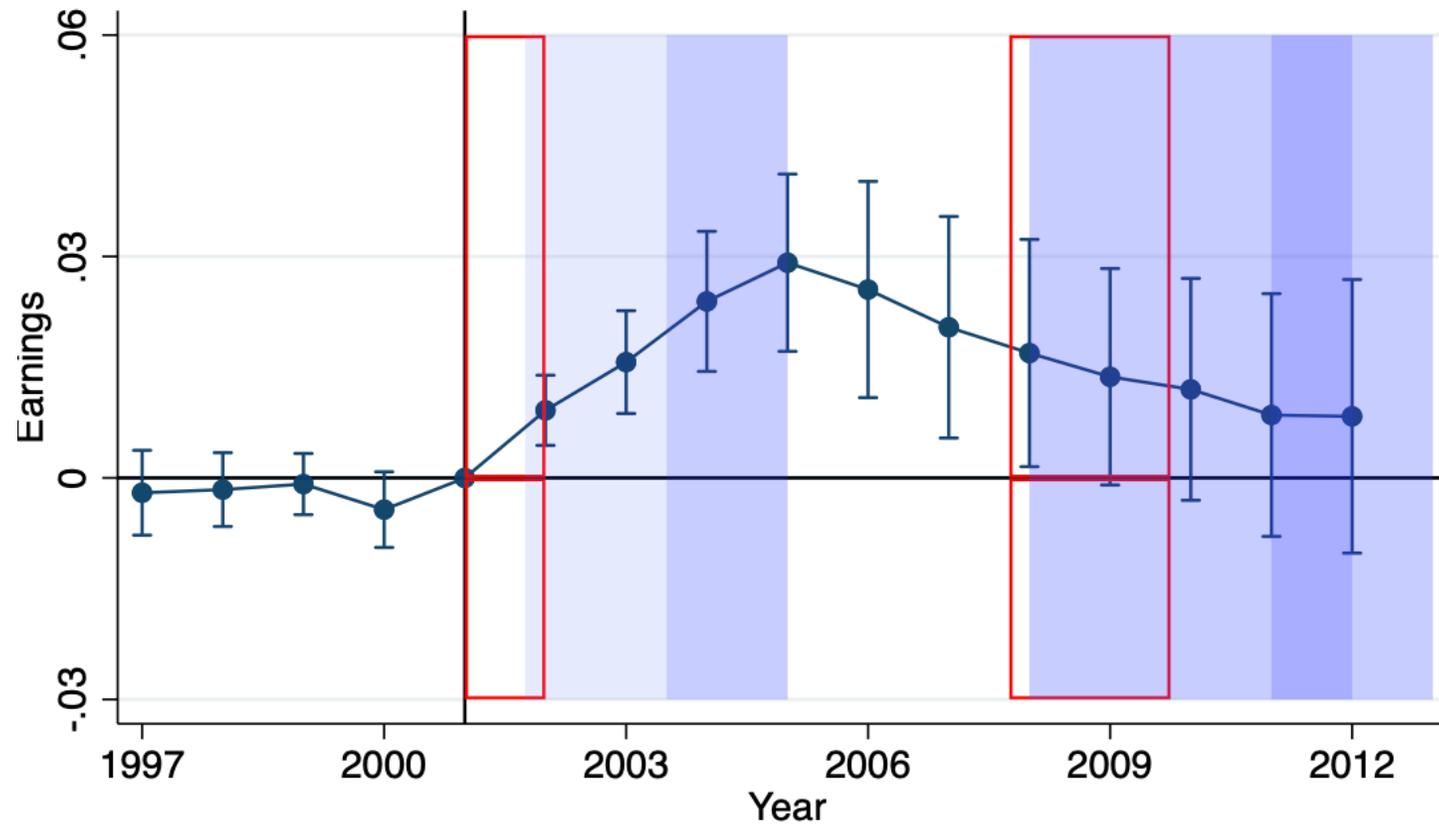

A. Employment

Impact of Depreciation Generosity on Local Labor Markets

B. Earnings

Impact of Depreciation Generosity on Local Labor Markets

C. Earnings-per-Worker

Legend:
- Long Duration Exposure
- Recession
- 50% Bonus
- 95% CI
- 30% Bonus
- 100% Bonus
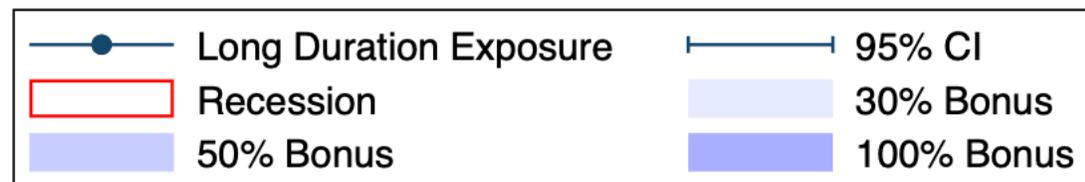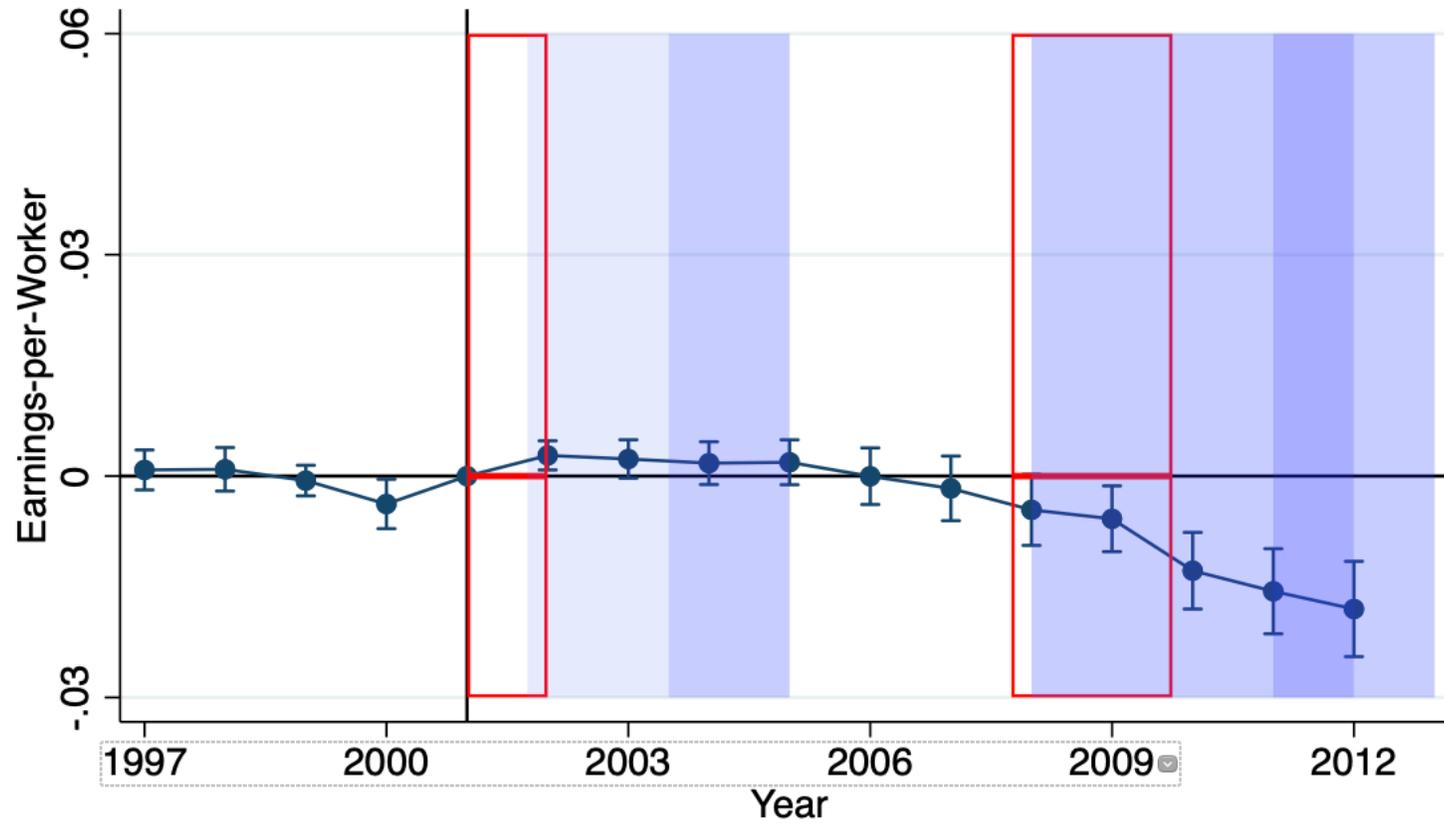
Placebo using "Structures and IP" exposure, which are not subject to bonus depreciation

D. Placebo
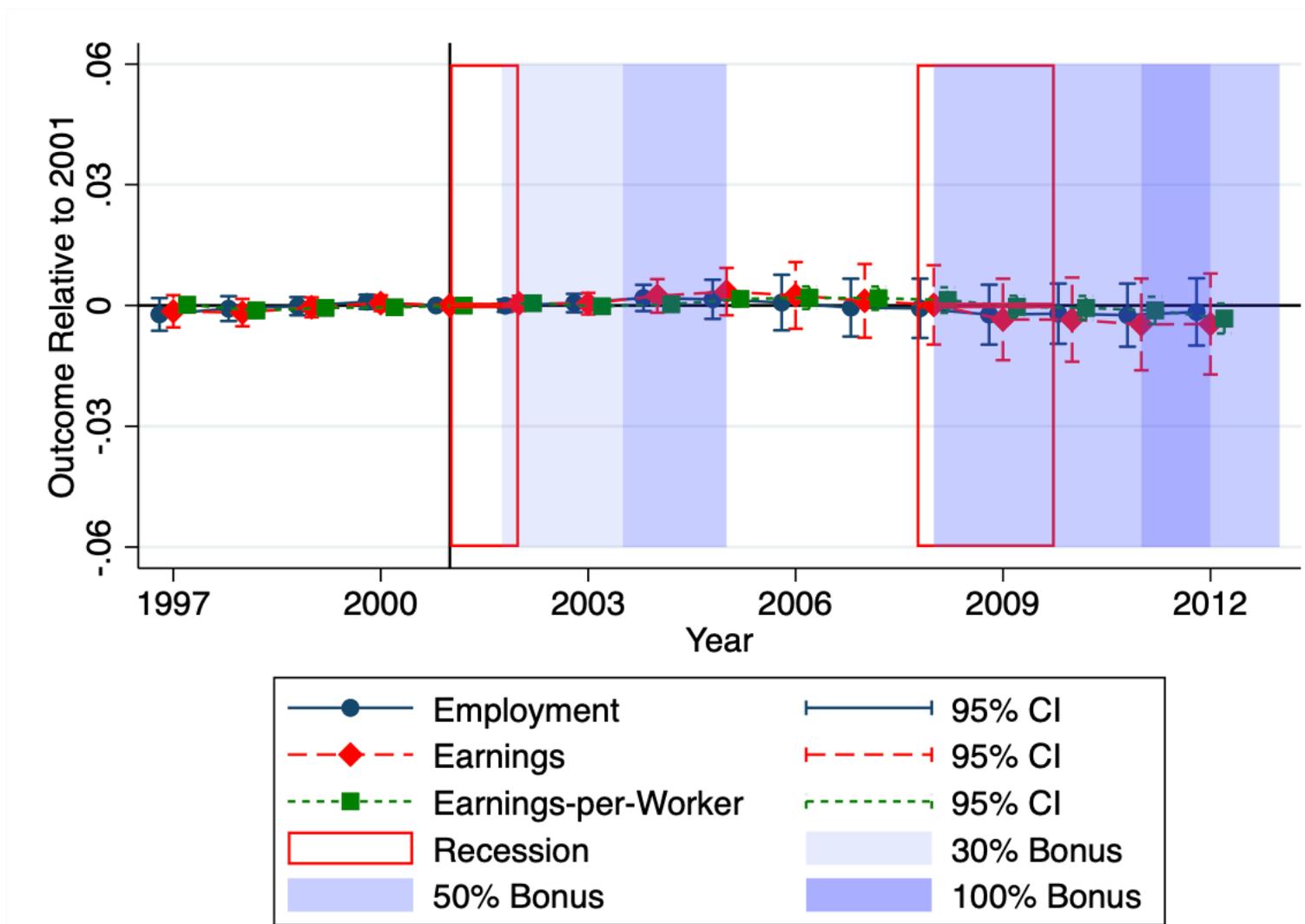
Summary

- Results suggest firms local investments leads to positive impacts on employment and local earnings

- Paper calculates a "$20,000 cost per job"

  - A common welfare metric – is this reasonable?

- What does this mean for models of perfect labor sorting? (e.g. Rosen-Roback?)

- Does this imply local workers benefit?

Housing Policy

- Many government spending and tax credits target housing and local development

- Consider two policies here:

  - Section 8 / Housing Choice Vouchers (Jacob and Ludwig 2012)

  - Hope VI – Laura Tach

- FYI there is a large literature on other policies, such as LIHTC (Diamond and McQuade 2017)

Housing Choice Voucher / Section 8 Program

- Housing Choice Vouchers provide subsidized rent to eligible families

- Family income may not exceed 50% of median income in county (preference given to those below 30%)

- No right to voucher – must apply and allocated based on preferential lottery

- Voucher holders pay 30% of income on rent

  - Leads to additional tax on earnings

- Jacob and Ludwig (2012) study impact on labor supply

Figure III: ITT Effect Of Vouchers Over Time On Residential Stability and Neighborhood Environment
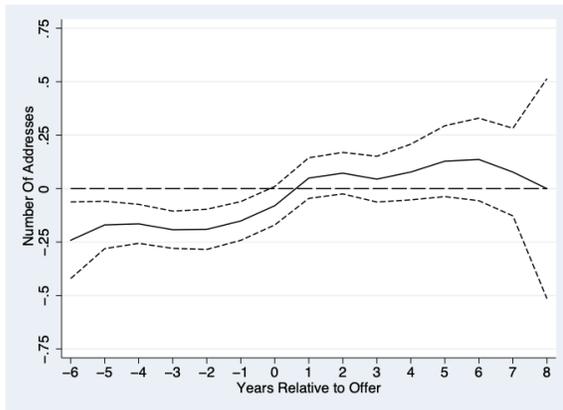
(a) Number Of Different Residential Addresses
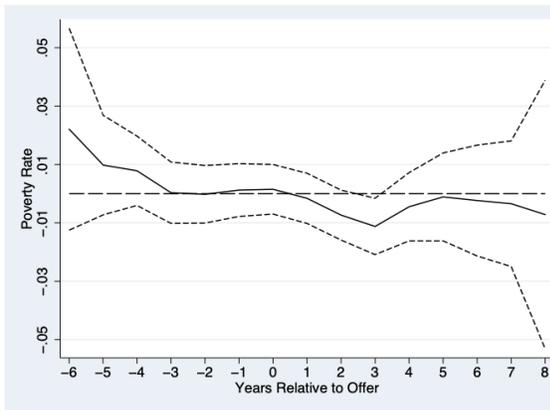
(b) Neighborhood Poverty Rate
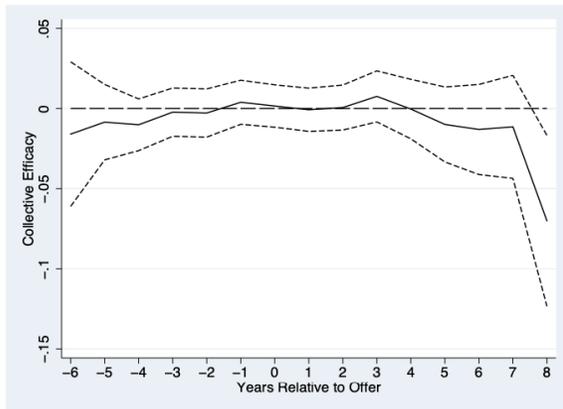
(c) Collective Efficacy Score
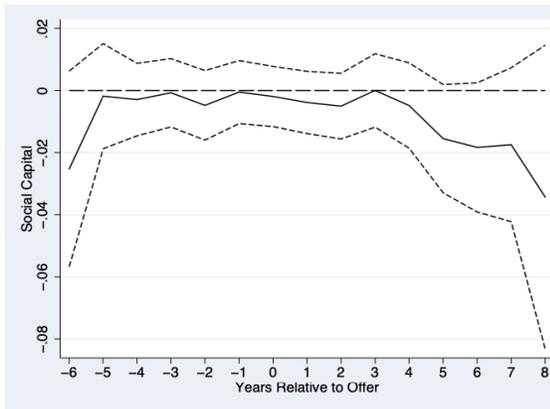
(d) Social Capital Score
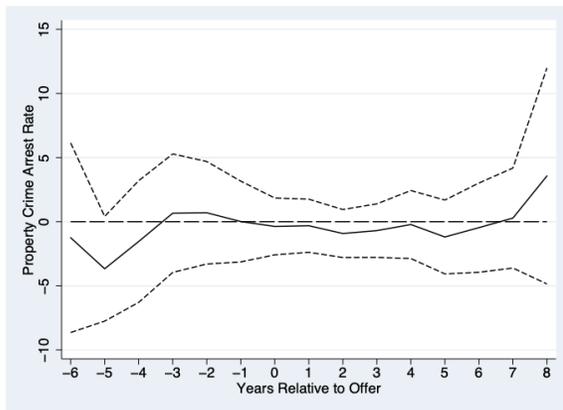
(e) Property Crime Arrest Rate
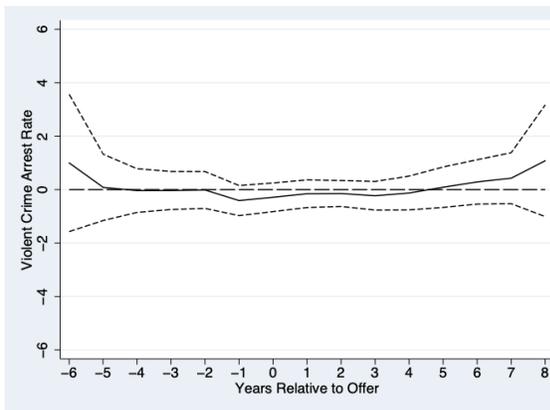
(f) Violent Crime Arrest Rate

Figure II: ITT Effect Of Vouchers Over Time On Employment And Receipt Of Public Assistance
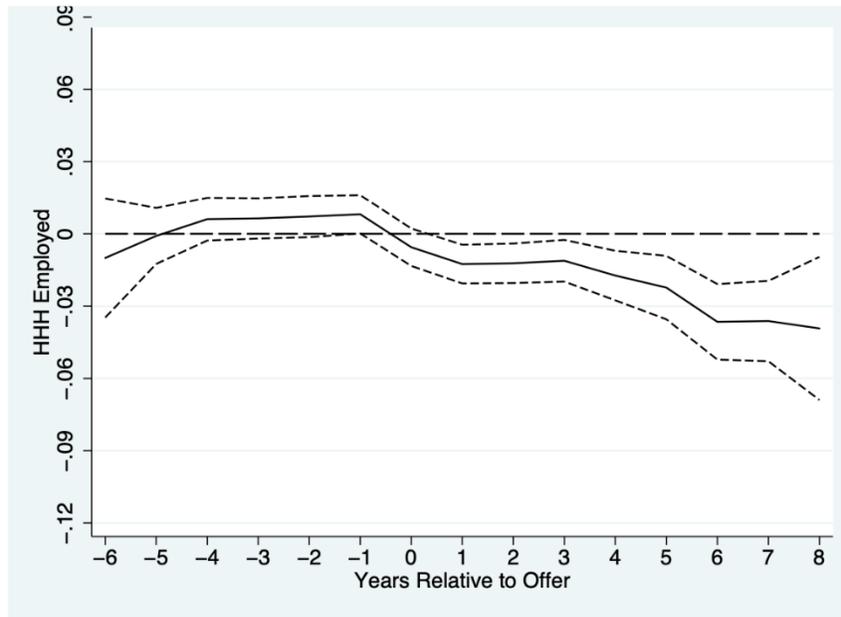
(a) HHH Employed
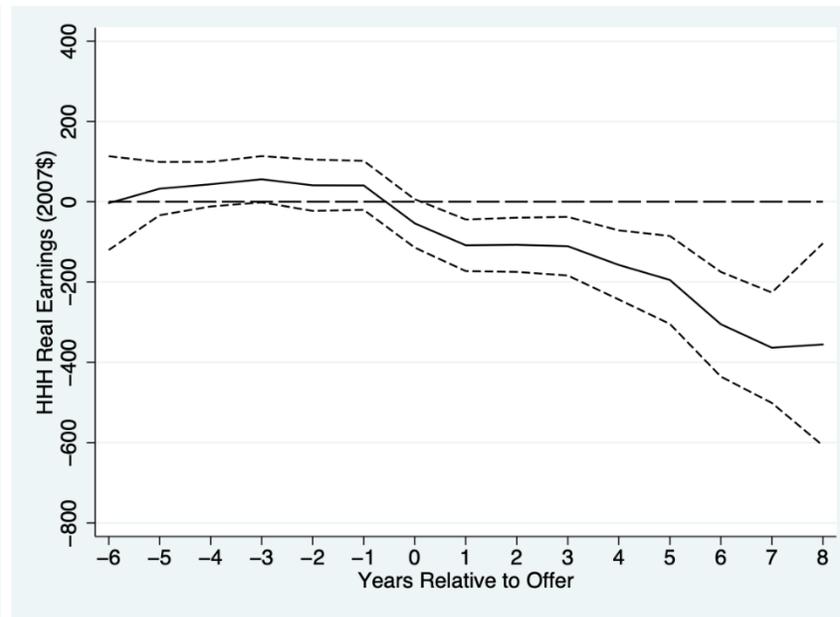
(b) HHH Real Earnings (2007$)
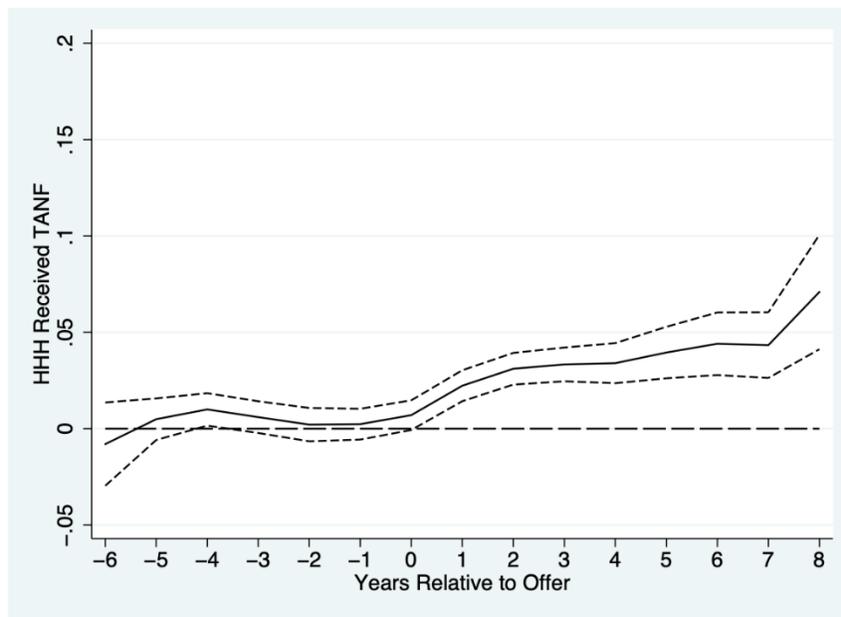
(c) HHH Receiving Any Public Assistance
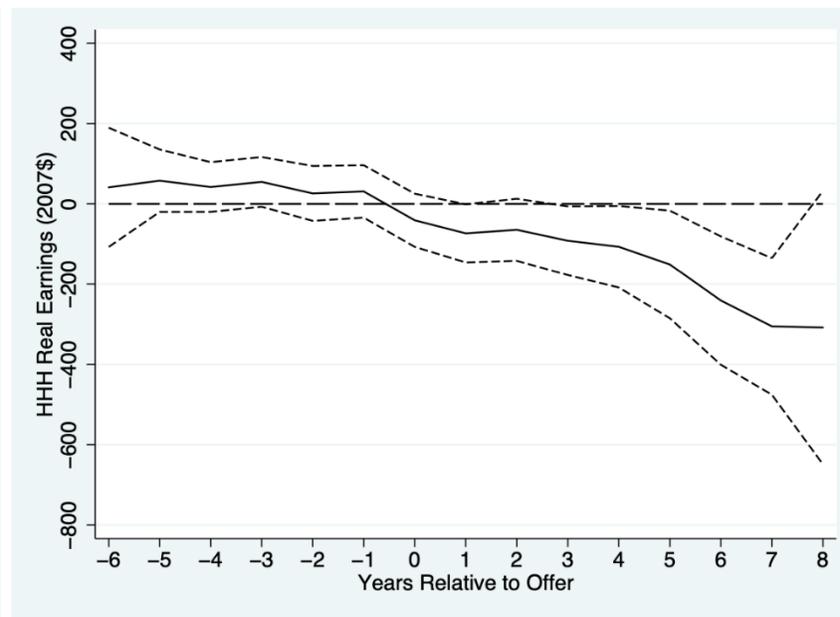
(d) HHH Conditional Earnings

Housing Choice Voucher / Section 8 Program

- Jacob, Kapustin, and Ludwig (2015) study impact on children

- No evidence of impacts on test scores, graduation, etc.

Housing Choice Voucher / Section 8 Program

TABLE III
Housing Voucher Effects on Education, Criminal Behavior, and Health

| | | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | | | | | | | ITT p-value | |
Baseline Age	Outcome	Children/obs.	CM	ITT	IV	CCM	Pair-wise	FDR
Male								
0–6	Test score	8,659 [51,339]	−0.3339	0.0369* (0.0190)	0.0634* (0.0325)	−0.3774	0.052	0.311
6–18	Test score	14,348 [68,787]	−0.3248	0.0068 (0.0152)	0.0126 (0.0273)	−0.3641	0.655	0.873
6–18	High school graduation	13,183 [13,183]	0.3940	0.0150 (0.0094)	0.0286 (0.0178)	0.4124	0.109	0.328
All	Social costs of crime	33,400 [283,091]	3,084	−161 (98)	−344* (206)	3,482	0.102	0.328
0–6	Inpatient or emergency claim	9,538 [52,378]	0.2449	−0.0012 (0.0063)	−0.0014 (0.0114)	0.2421	0.852	0.920
6–18	Inpatient or emergency claim	12,526 [56,480]	0.2471	−0.0059 (0.0060)	−0.0105 (0.0112)	0.2547	0.324	0.556

Place-based investment

- Results suggest no impact on "neighborhood quality" from Section 8 vouchers in Chicago

- Negative impacts on labor earnings and spillover impacts on public assistance

- Hendren and Sprung-Keyser (2020) calculate MVPF of 0.65

- No impacts on children (maybe something for youngest 0-6?)

  - Consistent with fact that vouchers didn't change where families moved

  - Recall evidence from MTO and CMTO from previous lecture suggests vouchers paired with services will change neighborhood locations

Place-based investment

- Tach and Emory ([2017 AJS](#)) study Hope VI, a program to revitalize the most distressed public housing units

- Generally involved destruction of existing public housing and building of new buildings

    - Existing residents were sometimes given vouchers or alternate locations

Place-based investment

$$X_{ijt} = \beta_1 + \beta_2(HOPEVI)_{ij} + \beta_3(Post)_{jt} + \beta_4(HOPEVI \times Post)_{ijt} \quad (1)$$

$$+ \beta_5(PScore)_{ij} + \alpha_j + \varepsilon_{ijt},$$

where X is one of our dependent variables (population share, population diversity, or population count) for block group i at time t (where t equals 1990, 2000, or 2010) in PHA j. For our analysis of block groups that contain public housing, HOPEVI is a dichotomous variable that equals one if the block group contains a public housing development that received a HOPE VI award, and zero if the block group contains a non–HOPE VI public housing development. *Post* is a dichotomous variable that equals zero before the grant was awarded and one after the grant was awarded.[15]

Hope VI: Poverty Rate
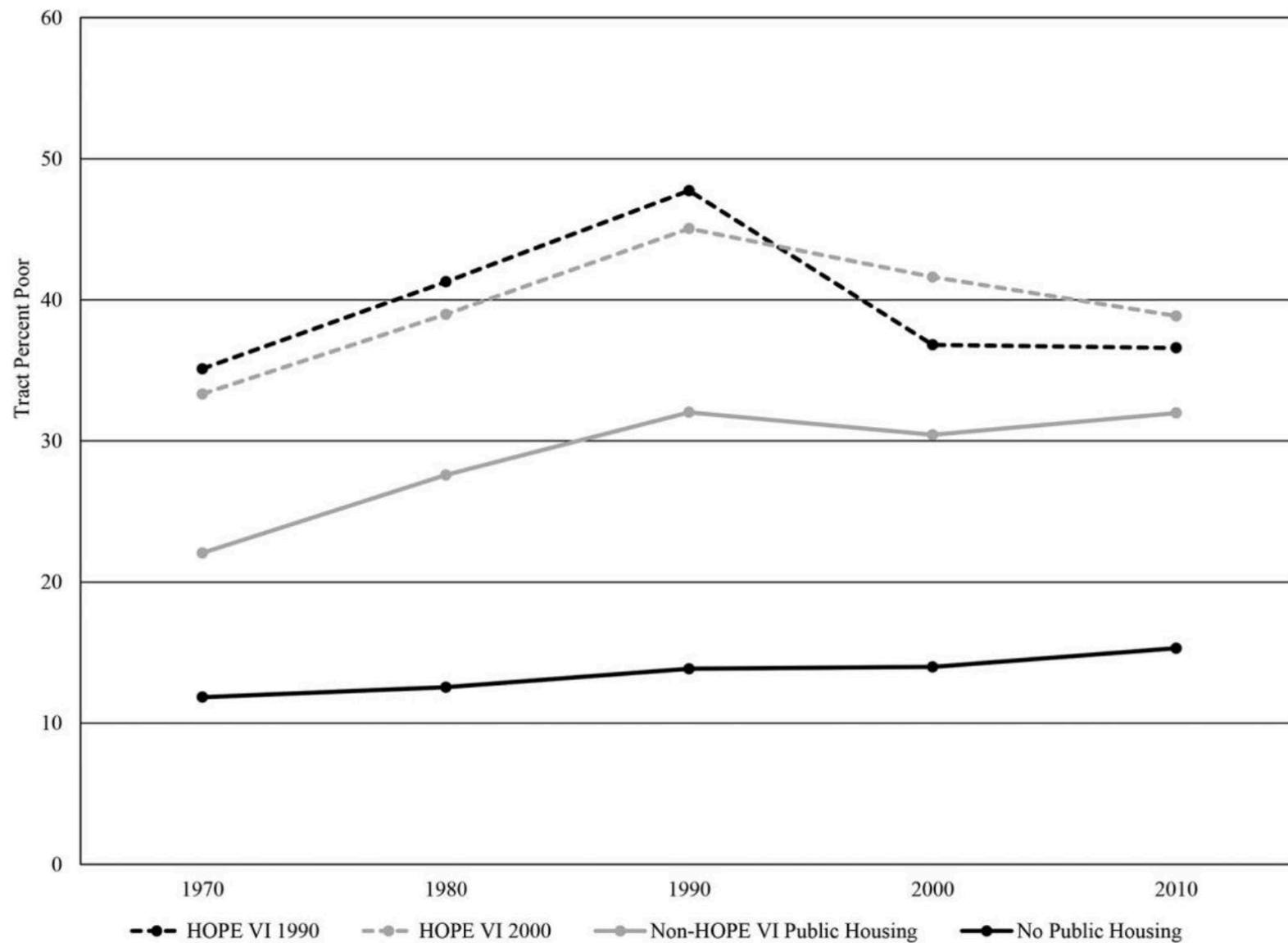
FIG. 1.—Average poverty rate in census tracts by presence of HOPE VI and public housing, 1970–2010

Hope VI: % White
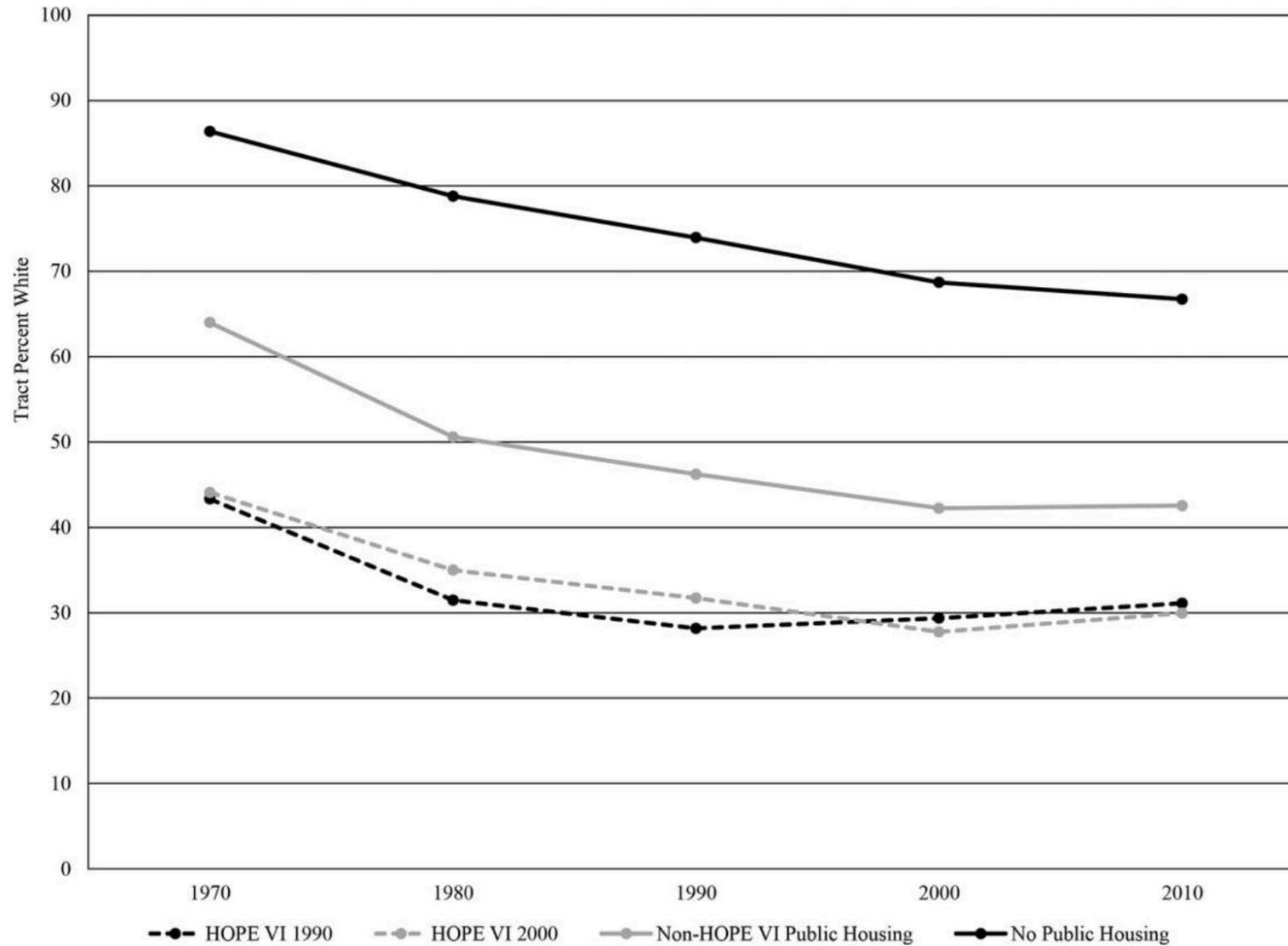
FIG. 2.—Average percentage of white residents in census tracts by presence of HOPE VI and public housing, 1970–2010

TABLE 2
Effect of HOPE VI Redevelopment on Poverty and Racial Composition in Block Groups Containing Public Housing, 1990–2010

	%Poor			%Non-Hispanic White		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Redeveloped in	1990s	1990s	2000s	1990s	1990s	2000s
Outcome in	2000	2010	2010	2000	2010	2010
Constant	33.70***	33.90***	31.80***	40.70***	40.63***	36.34***
	(.53)	(.55)	(.55)	(.90)	(.88)	(.82)
HOPE VI redevelopment	3.54**	3.79**	2.82*	−5.39**	−7.01**	−6.41**
	(1.30)	(1.33)	(1.36)	(1.73)	(1.71)	(1.68)
Post	−2.09***	−1.72***	1.32***	−6.46***	−8.05***	1.98***
	(.29)	(.43)	(.36)	(.25)	(.38)	(.22)
Post × HOPE VI	−9.71***	−10.90***	−9.64***	4.56***	8.64***	3.97***
	(1.25)	(1.49)	(1.69)	(.75)	(1.18)	(.85)
Propensity score	.51***	.47***	.55***	−.48***	−.41***	−.43***
	(.03)	(.03)	(.04)	(.04)	(.04)	(.04)
PHA fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Pretreatment tract trends in DV	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,394	4,394	3,944	4,394	4,394	3,944
R^2	.50	.41	.39	.56	.54	.59

Note.—Difference-in-differences regressions. SEs are clustered to account for multiple block groups per public housing development. Propensity scores are scaled from 0 to 100. DV = dependent variable, which is %poor in models 1–3 and %non-Hispanic white in models 4–6.

* $P<.05$.
** $P<.01$.
*** $P<.001$.

Hope VI Summary

- Results suggest Hope VI led to "revitalization" of local neighborhoods but displacement of existing low-income black residents

- No existing work has documented impact on pre-existing residents (although work is ongoing)

- Note Hope VI displacements led to increases in children's test scores:

  - Jacob (2004) finds impacts on test scores
  - Chyn (2018) documents impact of Hope VI demolitions on children

- Next lecture - Compare children whose parents' buildings are demolished vs. those who are not

Summary and Gentrification

- Summing up, Hope VI led to displacement of pre-existing residents

- Results next lecture will suggest positive effects on children and a "revitalization" or "gentrification" of the neighborhood

- Key question: what were the impacts on previous residents

Gentrification

- Burgeoning new work studying systematic impact of gentrification

- Brummet and Reed (2019) use linked census data to compare changes in outcomes for pre-existing residents to changes in neighborhood composition

- Measure "gentrification" as change in over-25 population % with bachelor's degree

$$gent_{jc} \equiv \frac{bachelors25_{jc,2010} - bachelors25_{jc,2000}}{total25_{jc,2000}} \ .$$

Figure 1: Gentrification in the Four Most Populous Metropolitan Areas
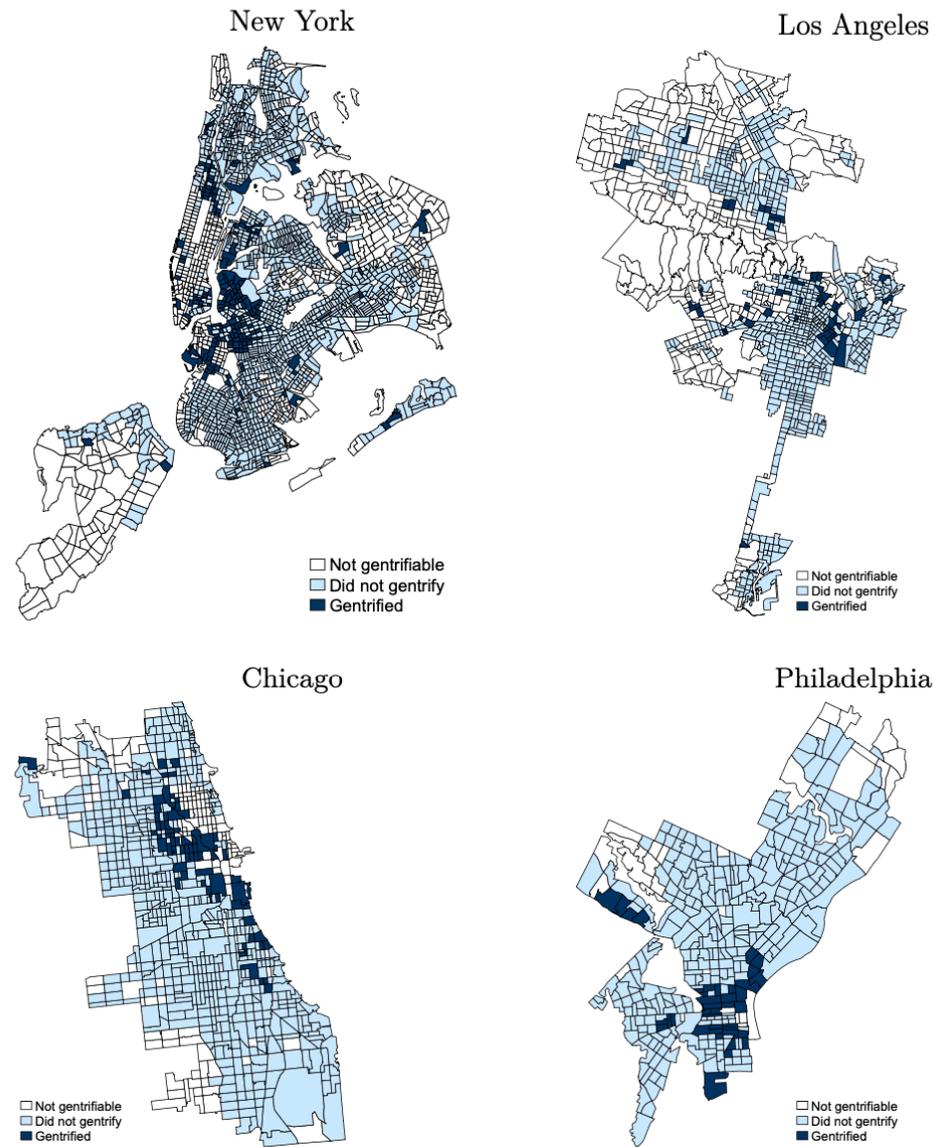
Notes: Population based on Core-Based Statistical Area (CBSA) in 2000. Gentrifiable tracts (light blue) are low-income census tracts of the largest central city in the CBSA. Gentrifying tracts (dark blue) are those in the top decile of our continuous gentrification measure. All numbers created using public use data in order to avoid disclosure issues. Source: Public use versions of the Census 2000 Long Form and 2010-2014 5-Year ACS Estimates.

Figure 2: Gentrification in the Four Most Gentrifying Central Cities

Washington, DC

Portland

- ☐ Not gentrifiable
- ☐ Did not gentrify
- ■ Gentrified

- ☐ Not gentrifiable
- ☐ Did not gentrify
- ■ Gentrified

Seattle

- ☐ Not gentrifiable
- ☐ Did not gentrify
- ■ Gentrified

Atlanta

- ☐ Not gentrifiable
- ☐ Did not gentrify
- ■ Gentrified
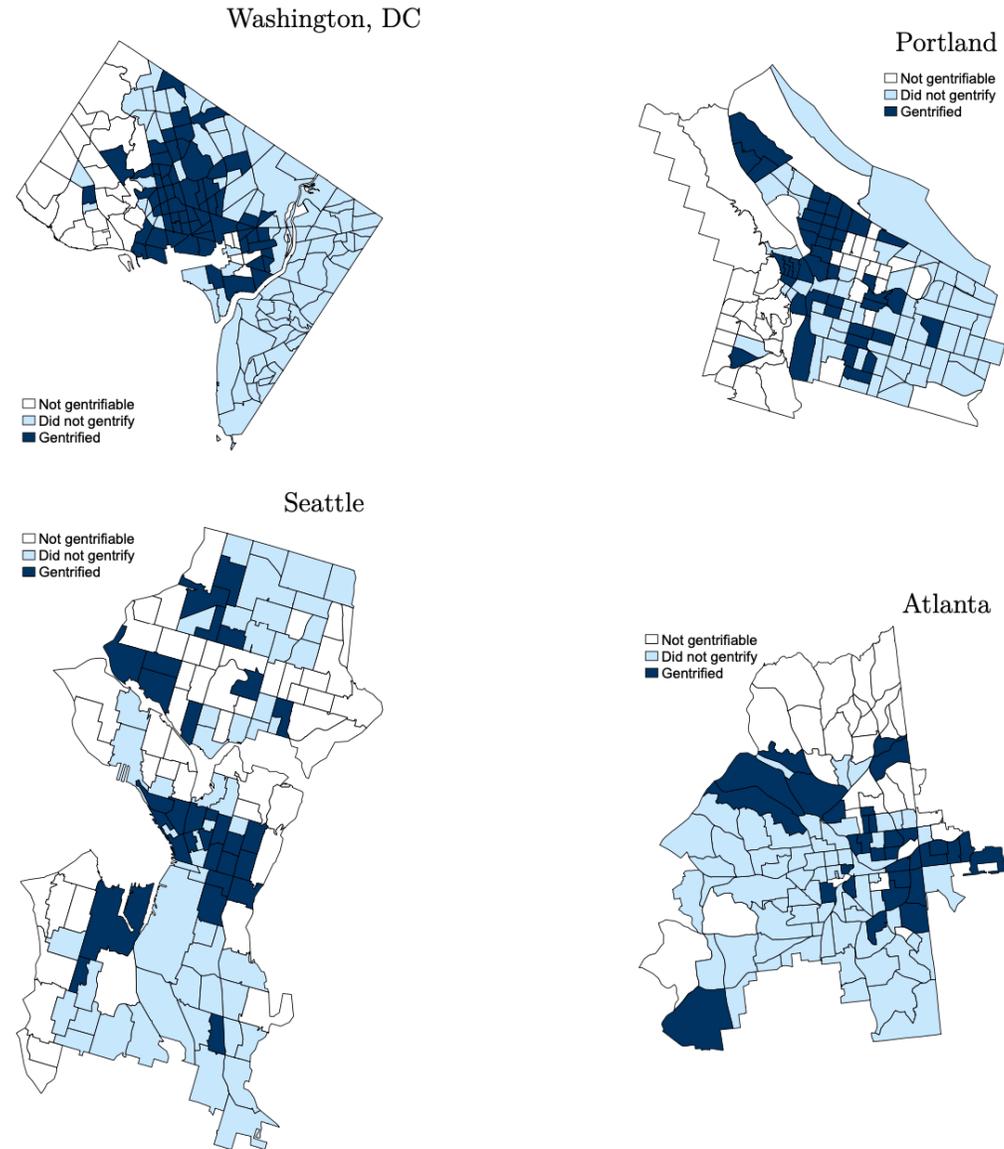
Notes: Most gentrifying central cities are defined as those with the highest shares of all gentrifiable neighborhoods that gentrified from 2000 to 2010-2014. Ordering is Washington, DC, Portland, Seattle, and Atlanta. Gentrifiable tracts (light blue) are low-income census tracts of the largest central city in the CBSA. Gentrifying tracts (dark blue) are those in the top decile of our continuous gentrification measure. Source: Public use versions of the Census 2000 Long Form and 2010-2014 5-Year ACS Estimates. All numbers created using public use data in order to avoid disclosure issues.

Table 5: Effect of Gentrification on Original Resident Adults
Among All Original Residents (Stayers and Movers)

	Less-Educated Renters		More-Educated Renters		Less-Educated Owners		More-Educated Owners	
	OLS	Oster	OLS	Oster	OLS	Oster	OLS	Oster
Move	0.0313***	0.043	0.0236***	0.0176	0.0252*	0.0282	0.0314***	0.0154
	(0.012)		(0.009)		(0.0152)		(0.0121)	
	0.183		0.211		0.117		0.148	
Move 1 mile	0.0479***	0.0662	0.0306***	0.0268	0.0292**	0.0316	0.0353***	0.0226
	(0.0128)		(0.00985)		(0.0149)		(0.0121)	
	0.182		0.208		0.115		0.143	
Exit CBSA	0.0400***	0.0456	0.0279**	0.0116	0.00306	0.00172	0.0114	-0.00429
	(0.0102)		(0.012)		(0.0092)		(0.0096)	
	0.0715		0.101		0.0468		0.058	
Tract poverty	-0.0328***	-0.0372	-0.0169***	-0.0118	-0.0351***	-0.0287	-0.0286***	-0.0177
	(0.00367)		(0.00267)		(0.00377)		(0.00317)	
	0.275		0.335		0.233		0.24	
Rent or house value	-11.23	-10.73	49.61**	45.63	16570***	12020	23830***	17990
	(15.48)		(22.01)		(6329)		(5870)	
	0.28		0.266		0.288		0.245	
Employment	-0.0082	-0.0103	-0.00362	0.0106	-0.0009	0.00251	-0.000416	0.00788
	(0.0173)		(0.0106)		(0.0224)		(0.0126)	
	0.441		0.391		0.437		0.372	
Income	-635.2	-929.1	-219.3	-1151	248.4	-332.7	3158**	2542
	(973.2)		(1187)		(1407)		(1596)	
	0.185		0.123		0.263		0.105	
Commute distance	-0.0271	-0.804	-2.315	-3.162	-0.576	-0.141	7.601	6.724
	(3.447)		(2.479)		(0.502)		(6.144)	
	0.216		0.336		0.647		0.334	
N	28,000		24,000		37,000		38,000	

Notes: Binary gentrification measure. All models include CBSA fixed effects and full controls: individual and household characteristics in 2000, tract characteristics in 2000, changes in tract characteristics from 1990 to 2000, and gentrification from 1990 to 2000. OLS standard errors in parentheses clustered at the tract level, followed by R-squared. Oster estimates described in Section 4.2. Numbers of individuals rounded to the nearest 1,000. Source: Census 1990 Long Form, Census 2000 Long Form, and 2010-2014 5-Year ACS Estimates. These results were disclosed by the US Census Bureau's Disclosure Review Board, authorization number CBDRB-FY19-397.

Table 7: Effect of Gentrification on Original Resident Children
Among All Original Residents (Stayers and Movers)

	Less-Educated Renters		More-Educated Renters		Less-Educated Owners		More-Educated Owners	
	OLS	Oster	OLS	Oster	OLS	Oster	OLS	Oster
Tract poverty	-0.0245***	-0.0293	-0.00762	-0.00862	-0.0241***	-0.0213	-0.0355***	-0.0287
	(0.0064)		(0.00675)		(0.00877)		(0.00597)	
	0.301		0.297		0.268		0.214	
Tract share college	0.0408***	0.0528	0.0356***	0.0471	0.0648***	0.0721	0.0714***	0.0711
	(0.00655)		(0.00776)		(0.011)		(0.00744)	
	0.203		0.254		0.135		0.139	
Tract employment	194.1***	157.6	75.12	22.5	255.4***	222.6	142.5***	98.64
	(50.94)		(47.26)		(66.62)		(49.85)	
	0.277		0.268		0.233		0.228	
Some college or more	-0.0116	-0.0297	0.0045	0.00664	0.0578	0.0635	0.00221	-0.0073
	(0.0261)		(0.0288)		(0.0383)		(0.0263)	
	0.11		0.142		0.132		0.133	
College degree or more	-0.0135	-0.0231	-0.0191	-0.0269	0.0499**	0.0406	-0.0343	-0.0503
	(0.0141)		(0.02)		(0.025)		(0.0226)	
	0.115		0.169		0.168		0.215	
Employment	-0.000181	-0.0000162	0.0395	0.0483	0.0276	0.0215	0.0172	0.0179
	(0.0273)		(0.0296)		(0.0382)		(0.026)	
	0.107		0.104		0.125		0.113	
Income	-892.9	-999.2	1442	1276	-446.1	-956.5	-245.1	-623.4
	(777.3)		(1107)		(1427)		(1151)	
	0.157		0.171		0.201		0.207	
N	14,500		11,000		7,500		13,500	

Notes: Binary gentrification measure. All models include CBSA fixed effects and full controls: individual and household characteristics in 2000, tract characteristics in 2000, changes in tract characteristics from 1990 to 2000, and gentrification from 1990 to 2000. OLS standard errors in parentheses clustered at the tract level, followed by R-squared. Oster estimates described in Section 4.2. Numbers of individuals rounded to the nearest 1,000. Source: Census 1990 Long Form, Census 2000 Long Form, and 2010-2014 5-Year ACS Estimates. These results were disclosed by the US Census Bureau's Disclosure Review Board, authorization number CBDRB-FY19-397.

Gentrification

- Evidence of:

- Displacement especially of low-income renters, statistically insignificant impact on employment and earnings.

- Positive impacts on house values for owners

- Exposure to poverty decreases for both owners and renters

- Some evidence of positive impacts on children, especially among owners

Summary

- Many open questions:

- Welfare impacts of "gentrification"? What's the right *definition* of "gentrification"

- Is place-based policy more "efficient" than national-based policy

  – Target people vs. places?
  – Fiscal externalities from local to national policies?
  – Optimal response to place-based "shocks" vs. level differences