Income Inequality, House Prices, and Housing Regulations

Chao Liu [1] Edmund Y. Lou [2] Wei Xiang [3]

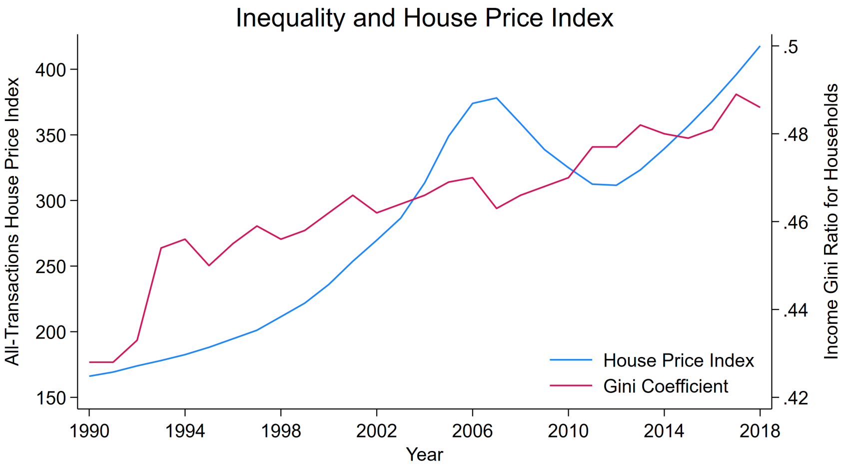
[1]Kellogg School of Management, Northwestern University

[2]Department of Economics, Northwestern University

[3]Department of Economics, Yale University

May 7, 2024

Income Inequality and House Prices in the U.S.



Note: Index 1980Q1=100.

This Paper

Research question 1

- Does income inequality have an impact on house prices?

Why should we care?

- Homeownership is a major source of wealth accumulation
- Housing wealth affects household consumption and borrowing behaviors

This Paper

Research question 1

- Does income inequality have an impact on house prices?

Why should we care?

- Homeownership is a major source of wealth accumulation
- Housing wealth affects household consumption and borrowing behaviors

Empirical challenges → Inconclusive evidence:

- Omitted variables: caveats of cross-country or cross-state analysis
- Reverse causality: migration due to rising house prices

This Paper

Research question 1

- Does income inequality have an impact on house prices?

Why should we care?

- Homeownership is a major source of wealth accumulation
- Housing wealth affects household consumption and borrowing behaviors

Empirical challenges → Inconclusive evidence:

- Omitted variables: caveats of cross-country or cross-state analysis
- Reverse causality: migration due to rising house prices

What do we do:

- Compile a panel of U.S. counties from 1990 to 2017
- Develop a Bartik-style instrumental variable for income inequality

This Paper

Research question 2

- How does income inequality affect house prices?

Mechanisms that have been proposed:

- Investment motives of the wealthy
- Housing demand of the poor

This Paper

Research question 2

- How does income inequality affect house prices?

Mechanisms that have been proposed:

- Investment motives of the wealthy
- Housing demand of the poor

What do we do:

- Document a high-price but low-quantity equilibrium
- Propose a supply-side channel

The Billionaire's Dilemma

Marc Andreessen says he's all for more new housing, but public records tell a different story.

- *It's Time to Build...crazily skyrocketing housing prices in places like San Francisco, making it nearly impossible for regular people to move in and take the jobs of the future.*

The Billionaire's Dilemma

Marc Andreessen says he's all for more new housing, but public records tell a different story.

- *It's Time to Build...crazily skyrocketing housing prices in places like San Francisco, making it nearly impossible for regular people to move in and take the jobs of the future.*
- *Please IMMEDIATELY REMOVE all multifamily overlay zoning projects from the Housing Element which will be submitted to the state in July.*
  They will MASSIVELY decrease our home values, the quality of life of ourselves and our neighbors and IMMENSELY increase the noise pollution and traffic.

This Paper

Research question 2

- How does income inequality affect house prices?

Mechanisms that have been proposed:

- Investment motives of the wealthy
- Housing demand of the poor

What do we do:

- Document a high-price but low-quantity equilibrium
- Propose a supply-side channel
- Estimate effect on housing regulations and supply

Preview of Results

A one standard deviation ↑ in the Gini coefficient (0.036) leads to

- House prices ↑ 26%
- Housing units ↓ 14%
- Wharton Residential Land Use Regulation Index in 2018 ↑ 0.35 standard deviation
- Building permits in the following decade ↓ 58%
- Homeownership rate ↓ 2 pp

Related Literature

- Income inequality and housing market:
  - Nakajima '05, Gyourko et al. '13, Määttänen & Terviö '14, Zhang '16, Kösem '23
  - Estimate the causal effect of income inequality on house prices
  - Propose a new supply-side channel through which inequality affects house prices
- Causes and consequences of housing regulations:
  - Glaeser et al. '05, Glaeser & Ward '09, Glaeser & Gyourko '18, Parkhomenko '23
  - Study inequality as a source of housing regulations
- Socioeconomic effect of income inequality:
  - Kennedy et al. '98, Fajnzylber et al. '02, Boustan et al. '15, Enamorado et al. '16
  - Develop a new instrumental variable for the Gini coefficient

Outline

- **Data**
- **Stylized Facts**
- **Income Inequality and House Prices**
- **A Supply-Side Mechanism**
- **Conclusion**

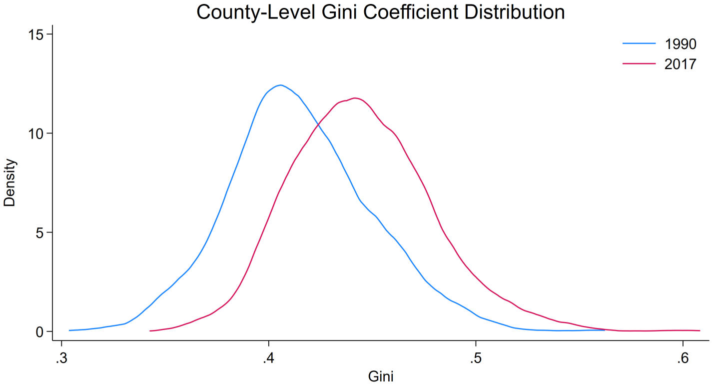
Data

Data

Sample: U.S counties in 1990, 2000, 2010 (2008-2012), and 2017 (2015-2019)

Data sources:

- Inequality: Census Historical Income Tables (1990 and 2000) and ACS (2010 and 2017)



▸ Other Measures

Data

Sample: U.S counties in 1990, 2000, 2010 (2008-2012), and 2017 (2015-2019)

Data sources:

- Inequality: Census Historical Income Tables (1990 and 2000) and ACS (2010 and 2017)
- House prices: FHFA Annual House Price Index (HPI)
- Housing supply: Building Permits Survey
- Housing regulation: Wharton Residential Land Use Regulation Index (Gyourko et al. '08, 21)
- Supplemental data:
  - Other local characteristics: Census and ACS summary files
  - Mortgage origination: HMDA
  - Land unavailability: Lutz and Sand '19

Summary Statistics

Stylized Facts

Binned Scatter Plots

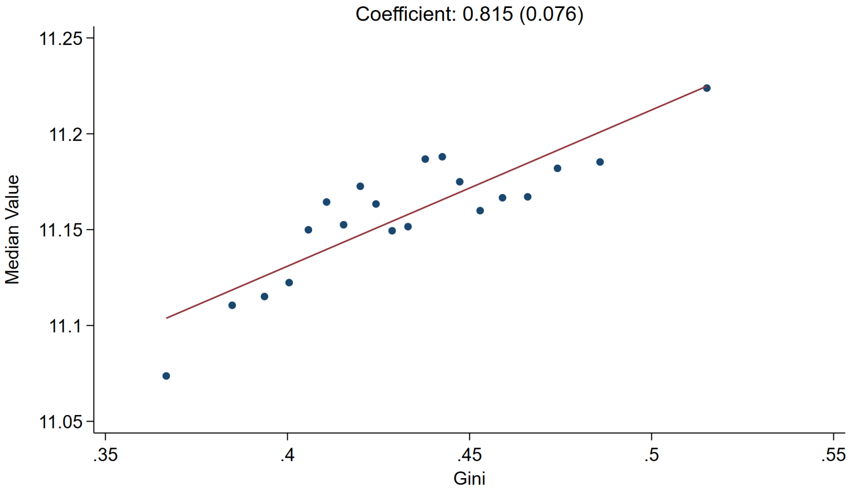
Pooled correlation

- Adjust nominal variables to 1990 dollars
- Control for real average income and population if necessary

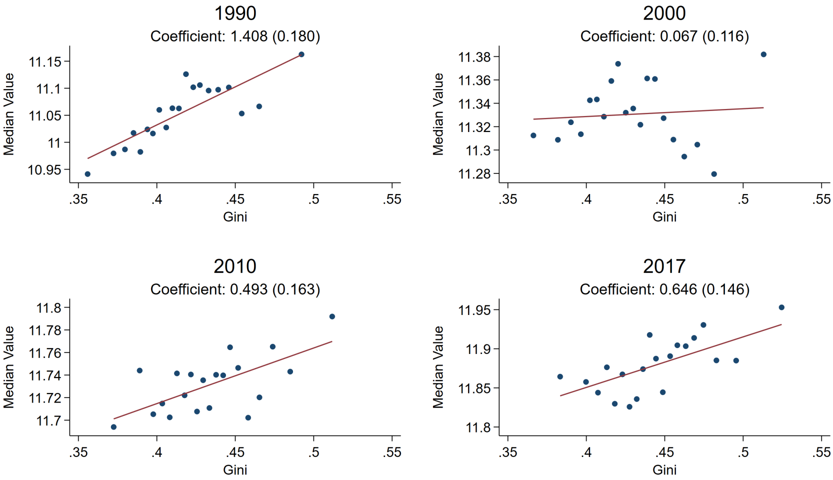
Repeated cross-sectional correlation

- Four time periods: 1990, 2000, 2010, and 2017
- Control for average income and population if necessary

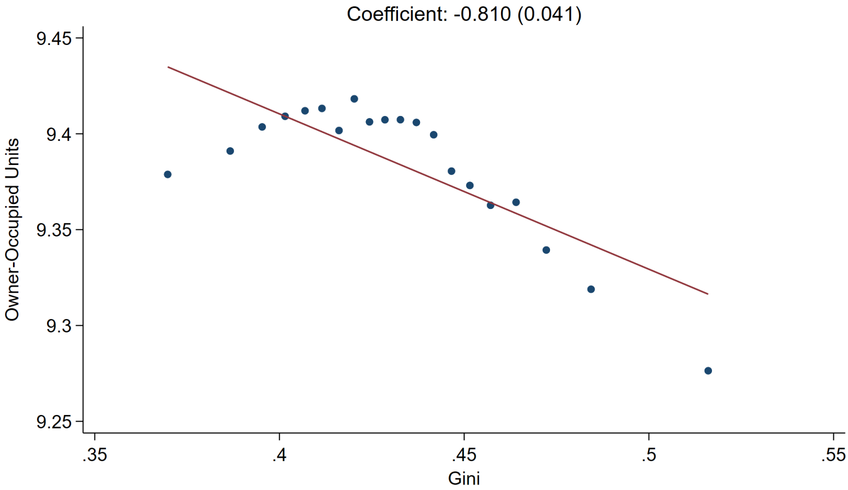
Fact I: Positive Correlation between Inequality and Housing Value



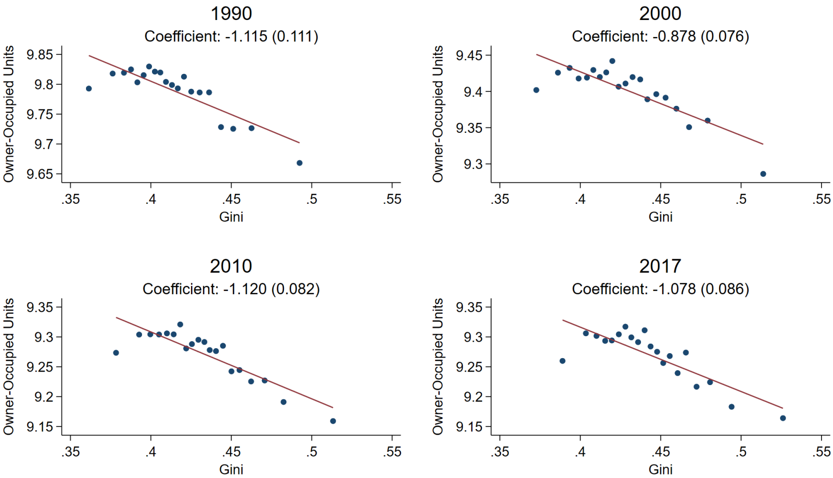
Fact I: Positive Correlation between Inequality and Housing Value



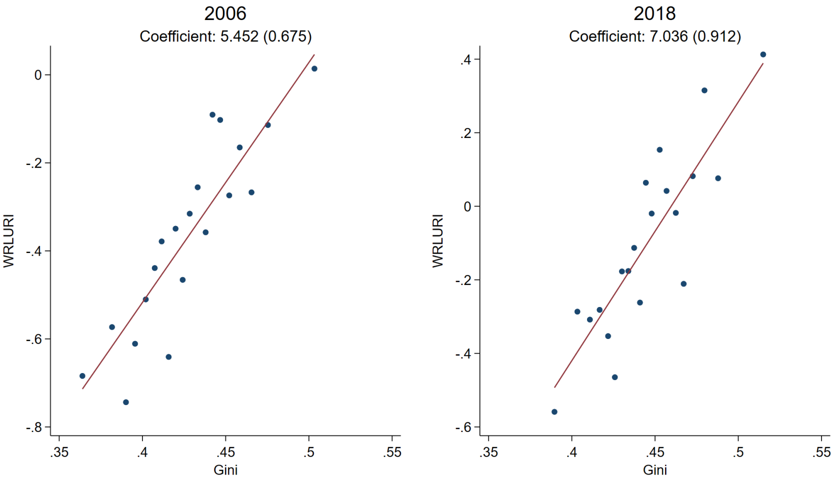
Fact II: Negative Correlation between Inequality and Housing Stocks



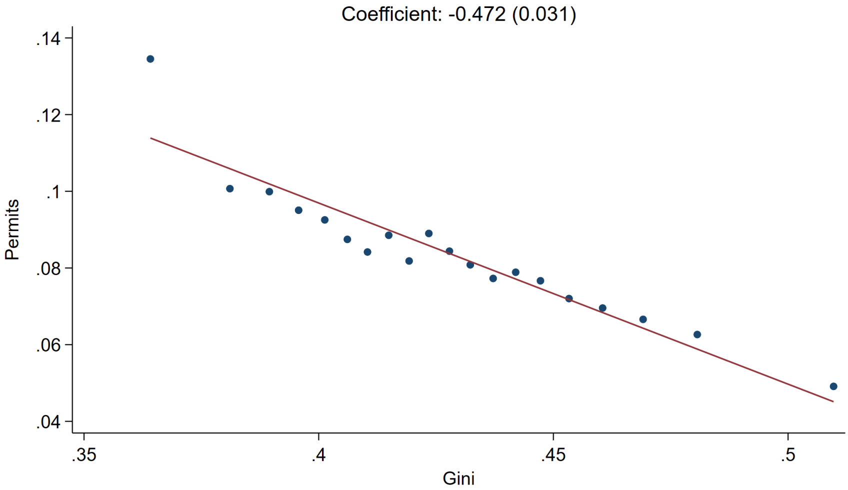
Fact II: Negative Correlation between Inequality and Housing Stocks



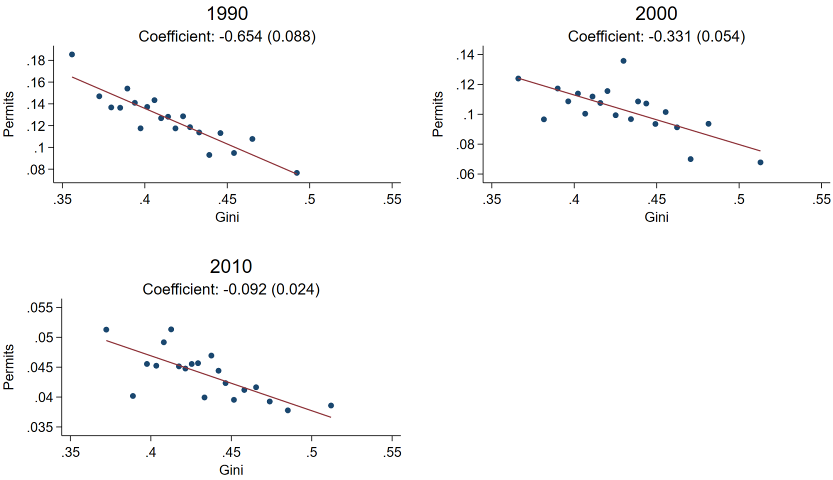
Fact III: Positive Correlation between Inequality and Housing Regulations



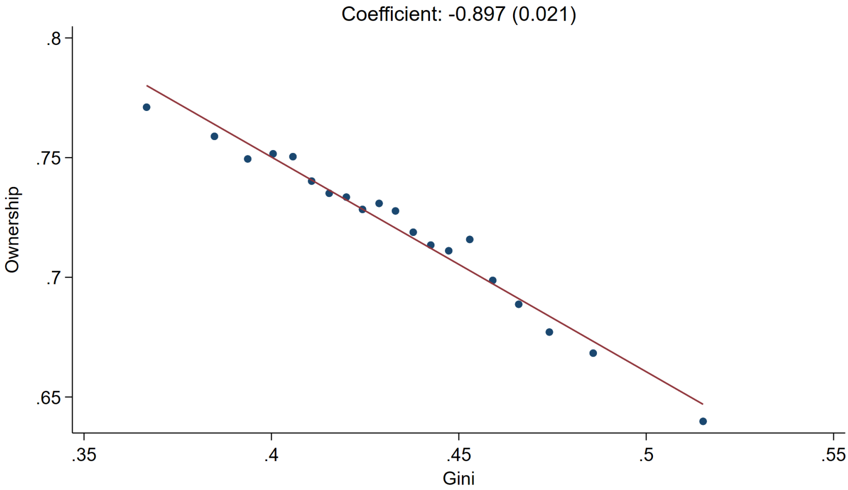
Fact IV: Negative Correlation between Inequality and Housing Supply



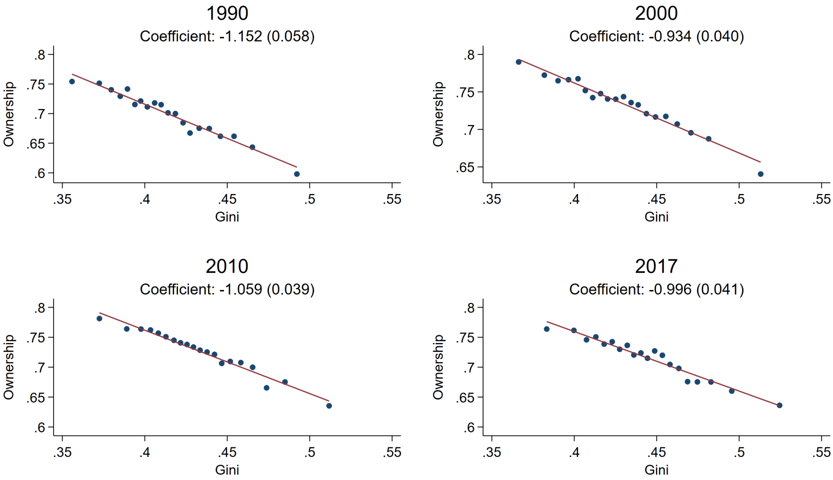
Fact IV: Negative Correlation between Inequality and Housing Supply



Fact V: Negative Correlation between Inequality and Homeownership



Fact V: Negative Correlation between Inequality and Homeownership



Income Inequality and House Prices

County-level Panel Regression

The OLS model is the following:

$$log(HPI_{ct}) = \alpha + \beta Inequality_{ct} + \Gamma X_{ct} + \delta_c + \delta_{st} + \varepsilon_{ct}, \tag{1}$$

where

- c represents county, s represents state, and $t = 1990, 2000, 2010, 2017$
- X_{ct}: mean income, population, minority share, unemployment rate, educational level
- δ_i, δ_{st}: county fixed effects and state-year fixed effects

Threat to Identification: Reverse Causality

House prices may have an impact on income inequality

- Rising house prices may push low income people to more affordable areas

  $\Longrightarrow$ local income inequality $\downarrow$ $\Longrightarrow$ OLS estimates downward biased
- Rising house prices may attract high income people

  $\Longrightarrow$ local income inequality $\uparrow$ $\Longrightarrow$ OLS estimates biased ambiguously

Threat to Identification: Reverse Causality

House prices may have an impact on income inequality

- Rising house prices may push low income people to more affordable areas

  $\Longrightarrow$ local income inequality $\downarrow$ $\Longrightarrow$ OLS estimates downward biased
- Rising house prices may attract high income people

  $\Longrightarrow$ local income inequality $\uparrow$ $\Longrightarrow$ OLS estimates biased ambiguously

We estimate the following equation:

$$Inequality_{ct} = \alpha_r + \beta_r log(HPI_{ct}) + \Gamma_r X_{ct} + \delta_c + \delta_t + \varepsilon_{ct} \tag{2}$$

- Use $log(HPI_{national,t}) \times LandUnavailability_c$ as the instrument for $log(HPI_{ct})$

Reverse Causality: Effect of House Prices on Income Inequality

Dependent variable	Poverty rate		Top 20% share		Gini	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
log(HPI)	-0.019** (0.008)	-0.062** (0.026)	-0.017*** (0.003)	-0.034*** (0.009)	-0.019*** (0.003)	-0.027** (0.011)
Observations	9,198	9,198	9,198	9,198	9,198	9,198
F statistic		52.785		52.785		52.785
County controls	✓	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓	✓

Increasing house prices have a negative effect on income inequality

$\Rightarrow$ OLS estimates of the effect of inequality on house prices downward biased

First-stage

A New Instrument for the Gini Coefficient

Bartik-style IV: predicted Gini coefficient

- Construct a predicted income distribution (Boustan et al. '13)
- Share component: initial tallies of households by income level in a locality
  - Occupation $\times$ Income percentile $\Longrightarrow$ Increase predictive power
- Shift component: national income growth by income bin
  - Leave-one-out for each state $\Longrightarrow$ Mitigate local bias
- Cannot be influenced by mobility into and out of counties

Instrument Construction Example: Cook County, IL

Initial local share: the share of one occupation with one income level in 1980

- Step 1a: Start from the county-level employment of 15 occupation in 1980

Occupation	Population
Executive and managerial occupations	257,626
Professional specialty occupations	289,086
Administrative occupations	509,018
...	...
Military	2,704
Unemployed	189,937

In 1980, Cook County had 257,626 individuals employed in executive occupations

▸ Occupations

A Better Approximation of the Initial Income Distribution

Large variation within each occupation ⇒ Approximate the distribution better

- Step 1b: Exploit the national income distribution for each occupation in 1980 to divide the state-level occupation employment into 6 bins

State	Occupation	Group	Percentile	Share
IL	Executive and managerial	1	0-10	0.07
IL	Executive and managerial	2	10-30	0.16
IL	Executive and managerial	3	30-70	0.40
IL	Executive and managerial	4	70-90	0.24
IL	Executive and managerial	5	90-98	0.06
IL	Executive and managerial	6	98-100	0.07

7% of people with executive occupations in IL earned an income above the 98th percentile

Initial Shares

Share component: 90 occupation-income groups in 1980

- Step 1c: Generate the initial shares at the county level

State	Occupation	Group	Percentile	Population
IL	Executive and managerial	1	0-10	257,626×0.07
IL	Executive and managerial	2	10-30	257,626×0.16
IL	Executive and managerial	3	30-70	257,626×0.40
IL	Executive and managerial	4	70-90	257,626×0.24
IL	Executive and managerial	5	90-98	257,626×0.06
IL	Executive and managerial	6	98-100	257,626×0.07

18,034 households have executive occupations and earn above the 98th percentile in future

National Income Growth in Later Years

Shift component: national income growth in 1990, 2000, 2010, and 2017

- Step 2: Leave-one-out national income percentiles for each occupation in 1990

State	Occupation	p5	p20	p50	p80	p94	p99
IL	Executive	16,000	31,001	53,763	86,852	139,978	254,000
IL	Professional	15,000	30,010	51,000	80,362	126,900	229,716
IL	Administrative	11,626	22,728	40,000	62,494	91,190	154,700
...	...	...	...	...	...	...	...
IL	Military	12,100	18,918	30,220	48,733	72,000	109,000
IL	Unemployed	2,500	10,000	25,200	48,200	76,400	129,603

The national 99th percentile income (excluding IL) for executive occupations was \$254,000

A Predicted Local Income Distribution in Later Years

Predicted local income distribution: local share in 1980 and national income in 1990

- Step 3: Generate a predicted income distribution for each county in 1990

Group	Occupation	Percentile	Income	Household
1	Executive occupations	0-10	16,000	257,626$\times$0.07
2	Executive occupations	10-30	31,001	257,626$\times$0.16
3	Executive occupations	30-70	53,763	257,626$\times$0.40
4	Executive occupations	70-90	86,852	257,626$\times$0.24
5	Executive occupations	90-98	139,978	257,626$\times$0.06
6	Executive occupations	98-100	254,000	257,626$\times$0.07

18,034 households are predicted to earn $254,000 in Cook county in 1990

Predicted Gini Coefficient

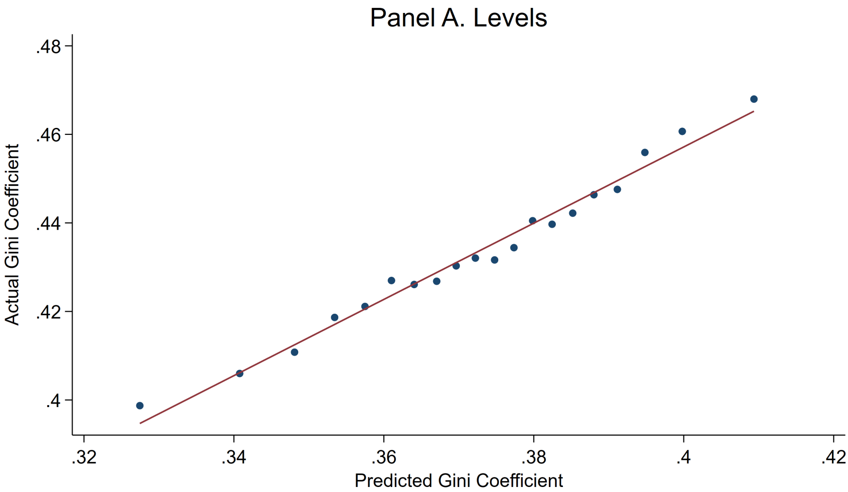
Bartik-style IV: the Gini coefficient based on the predicted income distribution

- Step 4: Use predicted grouped income to calculate the Gini coefficient

$$Gini_{ct}^{IV} = \frac{1}{2\bar{\tilde{W}}_{ct}} \sum_{i=1}^{K} \sum_{j=1}^{K} f_{ic,1980} f_{jc,1980} \left| \tilde{w}_{it,-s} - \tilde{w}_{jt,-s} \right| \tag{3}$$

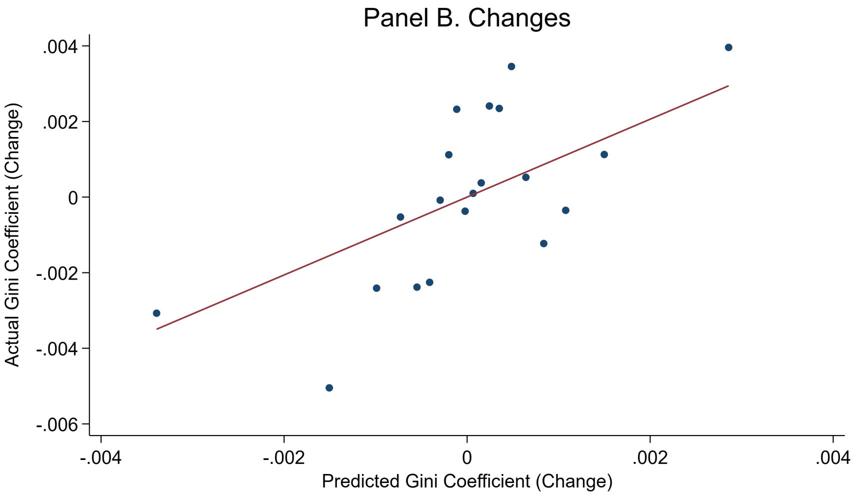
  - $K = 90$ (15 occupations $\times$ 6 income levels)
  - $\bar{\tilde{W}}_{ct}$: predicted mean income in county c in year t ($\sum_{i=1}^{K} f_{ic,1980} \tilde{w}_{it,-s}$)
  - $f_{ic,1980}$: employment share of group i in county c in 1980
  - $\tilde{w}_{it,-s}$: leave-one-out income level of group i in counties of state s in year t

First-Stage: Actual and Synthetic Gini Coefficient



Other Measures

First-Stage: Actual and Synthetic Gini Coefficient



▸ Other Measures

IV Results

Dependent variable	Gini	log(HPI)			
	First-stage	IV-all	IV-inelastic	IV-elastic	OLS-all
	(1)	(2)	(3)	(4)	(5)
Predicted Gini	0.926***				
	(0.153)				
Gini		7.215***	11.136***	3.688	-0.593***
		(2.135)	(4.025)	(2.784)	(0.211)
Observations	9,277	9,194	4,612	4,568	9,194
F statistic		35.569	20.382	9.921	
County controls	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓

A one s.d. $\uparrow$ in the Gini coefficient $\Rightarrow$ 26% higher house prices

▸ Top20 ▸ Mean 5/3 ▸ Drop 2010 ▸ Balanced ▸ MSA

Heterogeneous Effects Across Land Supply

Dependent variable	Gini	log(HPI)			
	First-stage (1)	IV-all (2)	IV-inelastic (3)	IV-elastic (4)	OLS-all (5)
Predicted Gini	0.926*** (0.153)				
Gini		7.215*** (2.135)	11.136*** (4.025)	3.688 (2.784)	-0.593*** (0.211)
Observations	9,277	9,194	4,612	4,568	9,194
F statistic		35.569	20.382	9.921	
County controls	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓

Larger effect in areas with inelastic land supply

OLS Results: Downward Biased

Dependent variable	Gini	log(HPI)			
	First-stage	IV-all	IV-inelastic	IV-elastic	OLS-all
	(1)	(2)	(3)	(4)	(5)
Predicted Gini	0.926***				
	(0.153)				
Gini		7.215***	11.136***	3.688	-0.593***
		(2.135)	(4.025)	(2.784)	(0.211)
Observations	9,277	9,194	4,612	4,568	9,194
F statistic		35.569	20.382	9.921	
County controls	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓

Consistent with Kösem ’23

Kösem OLS OLS Median

Discussion of Exclusion Restriction

Goldsmith-Pinkham et al. '20:

- Equivalence: Using the Bartik IV is equivalent to using initial shares as multiple IVs
- Estimator: A weighted sum of just-identified IV estimators
- Weights: Indicate the sensitivity of the IV estimate to misspecification (Rotemberg '83)
- Exogeneity: Interpret exogeneity conditions in terms of initial shares
- Guidance: Argue that shares with large weights are exogenous

Discussion of Exclusion Restriction

Goldsmith-Pinkham et al. '20:

- Equivalence: Using the Bartik IV is equivalent to using initial shares as multiple IVs
- Estimator: A weighted sum of just-identified IV estimators
- Weights: Indicate the sensitivity of the IV estimate to misspecification (Rotemberg '83)
- Exogeneity: Interpret exogeneity conditions in terms of initial shares
- Guidance: Argue that shares with large weights are exogenous
- Our IV: not in the form of an inner product

$$Gini_{ct}^{IV} = \frac{1}{2\bar{\tilde{W}}_{ct}} \sum_{i=1}^{K} \sum_{j=1}^{K} f_{ic,1980} f_{jc,1980} \left| \tilde{w}_{it,-s} - \tilde{w}_{jt,-s} \right|$$

Test 1

Drop some potentially influential groups

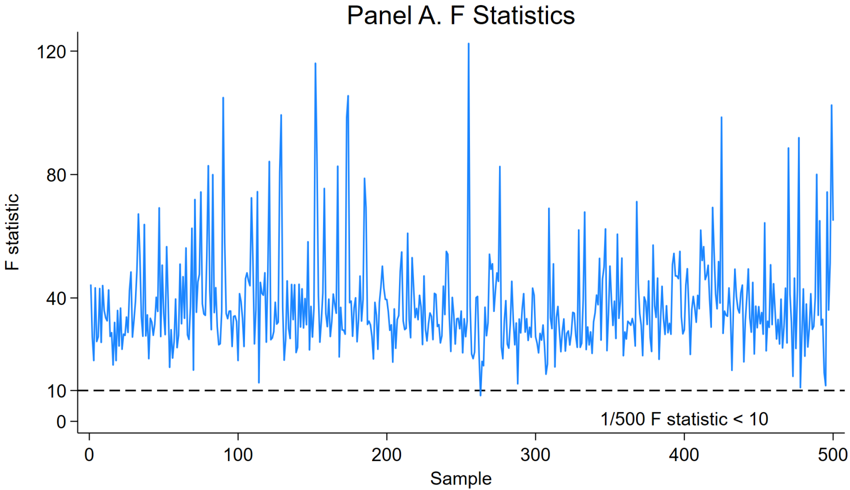
Dependent variable	log(HPI)				
	Use 90 groups (1)	Drop 10 highest (2)	Drop 10 lowest (3)	Drop 10 largest (4)	Drop 5 highest & 5 lowest (5)
Gini	7.215***	5.233***	7.739***	5.140***	7.234***
	(2.135)	(1.685)	(2.741)	(1.707)	(2.636)
Observations	9,194	9,194	9,194	9,194	9,194
F statistic	35.569	42.927	25.714	46.889	24.390
County controls	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓

Test 2

Use a random bundle of groups to generate instruments

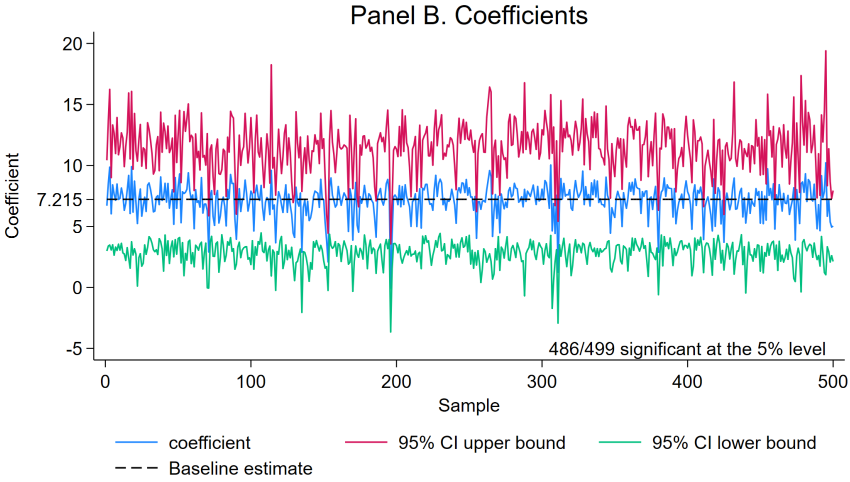
- Randomly choose 80 groups to predict the Gini coefficient
- Use this IV to re-estimate Equation (1)
- Repeat the above steps for 500 times
- The number of groups determines the tradeoff between
  - the first-state strength
  - the plausibility of the exclusion restriction

F-Statistics of Random IV (80 Groups)



▸ 70 Groups ▸ 60 Groups

IV Results Using Random IV (80 Groups)



▸ 70 Groups ▸ 60 Groups

Plausibility of IV

Test 1: Drop some potentially influential groups

Test 2: Use a random bundle of groups to generate instruments

$$\Downarrow$$

All initial shares contribute relatively equally to the overall identification

Plausibility of IV

Test 1: Drop some potentially influential groups

Test 2: Use a random bundle of groups to generate instruments

$\Downarrow$

All initial shares contribute relatively equally to the overall identification

$+$

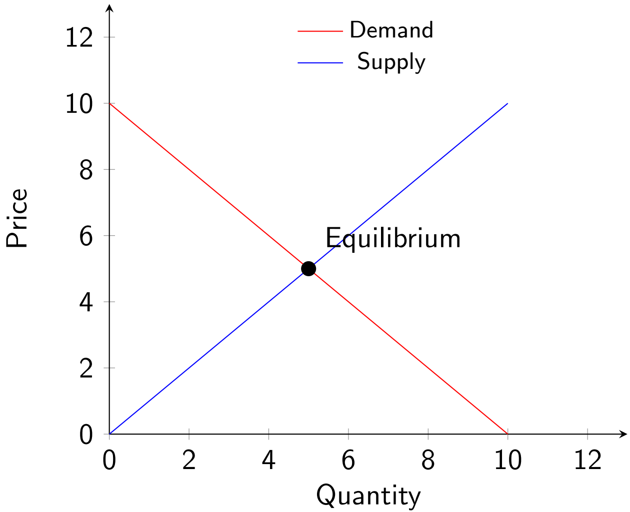
Some shares are likely to be exogenous: military workers

$\Downarrow$

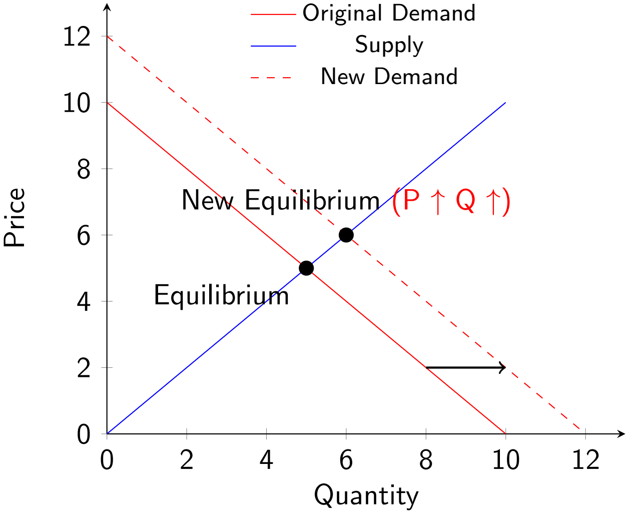
Plausibility of IV

Mechanism: Housing Regulations

A Simple Demand-Supply Framework



Why Solely Demand-Side Mechanisms Fail?



Demand

Effect on Housing Quantity

Dependent variable	log(Housing units)		log(Owner occupied units)		Housing units per capita	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Gini	0.244***	-3.910***	0.032	-3.612***	0.092***	-1.548***
	(0.044)	(0.893)	(0.074)	(0.835)	(0.020)	(0.357)
Observations	9,277	9,277	9,277	9,277	9,277	9,277
F statistic		36.568		36.568		36.568
County controls	✓	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓	✓

Reverse causality: Sufficient housing units $\Rightarrow$ Higher Gini coefficients

▸ Reverse Causality

Effect on Housing Quantity

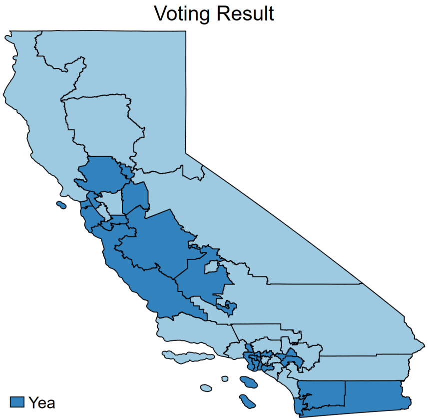
Dependent variable	log(Housing units)		log(Owner occupied units)		Housing units per capita	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Gini	0.244***	-3.910***	0.032	-3.612***	0.092***	-1.548***
	(0.044)	(0.893)	(0.074)	(0.835)	(0.020)	(0.357)
Observations	9,277	9,277	9,277	9,277	9,277	9,277
F statistic		36.568		36.568		36.568
County controls	✓	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓	✓

A one s.d. $\uparrow$ in the Gini coefficient $\Rightarrow$ 14% fewer housing units

Higher prices and fewer stocks $\Rightarrow$ Need a supply-side mechanism

A Case Study: California Senate Bill 35

- Introduced in December 2016
- Enacted in September 2017
- Streamline the approval process for multi-family projects
- Result: Yea 23; Nay 14; NV 3



Inequality and the Voting Result of SB 35

Dependent variable		$\mathbb{1}$(Yea)	
	(1)	(2)	(3)
Gini	-7.874**		
	(3.831)		
Top 20 share		-7.760*	
		(4.300)	
Top 5 share			-10.373**
			(4.335)
Observations	37	37	37
Legislative District Controls	✓	✓	✓

The higher the level of inequality, the lower the support for SB 35

Effect on Housing Regulation in 2006

LPPI06: local political pressure index (standardized)

Dependent variable	LPPI06		SRI06		WRLURI06	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Gini	0.458	15.317**	-2.882	6.599**	-0.111	13.497**
	(2.172)	(5.752)	(2.232)	(3.070)	(1.633)	(5.523)
Observations	825	825	825	825	825	825
F statistic		30.641		30.641		30.641
County controls	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓

A one s.d. ↑ in the Gini coefficient ⇒ A 0.64 standard deviation ↑ in LPPI

Effect on Housing Regulation in 2006

SRI06: supply restrictions index (ranging from 0 to 6)

Dependent variable	LPPI06		SRI06		WRLURI06	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Gini	0.458	15.317**	-2.882	6.599**	-0.111	13.497**
	(2.172)	(5.752)	(2.232)	(3.070)	(1.633)	(5.523)
Observations	825	825	825	825	825	825
F statistic		30.641		30.641		30.641
County controls	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓

A one s.d. $\uparrow$ in the Gini coefficient $\Rightarrow$ A 0.34 standard deviation $\uparrow$ in SRI

Effect on Housing Regulation in 2006

WRLURI06: Wharton residential land use regulatory index (standardized)

Dependent variable	LPPI06		SRI06		WRLURI06	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Gini	0.458	15.317**	-2.882	6.599**	-0.111	13.497**
	(2.172)	(5.752)	(2.232)	(3.070)	(1.633)	(5.523)
Observations	825	825	825	825	825	825
F statistic		30.641		30.641		30.641
County controls	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓

A one s.d. $\uparrow$ in the Gini coefficient $\Rightarrow$ A 0.57 standard deviation $\uparrow$ in WRLURI

Effect on Housing Regulation in 2018

LPPI18: local political pressure index (ranging from 3 to 15)

Dependent variable	LPPI18		SRI18		WRLURI18	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Gini	-0.030	23.296***	-0.865	5.041**	-1.064	10.045**
	(2.263)	(7.208)	(1.657)	(2.142)	(2.390)	(4.012)
Observations	841	841	841	841	841	841
F statistic		20.710		20.710		20.710
County controls	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓

A one s.d. $\uparrow$ in the Gini coefficient $\Rightarrow$ A 0.4 standard deviation $\uparrow$ in LPPI

Effect on Housing Regulation in 2018

SRI18: supply restrictions index (ranging from 0 to 6)

Dependent variable	LPPI18		SRI18		WRLURI18	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Gini	-0.030	23.296***	-0.865	5.041**	-1.064	10.045**
	(2.263)	(7.208)	(1.657)	(2.142)	(2.390)	(4.012)
Observations	841	841	841	841	841	841
F statistic		20.710		20.710		20.710
County controls	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓

A one s.d. $\uparrow$ in the Gini coefficient $\Rightarrow$ A 0.27 standard deviation $\uparrow$ in SRI

Effect on Housing Regulation in 2018

WRLURI18: Wharton residential land use regulatory index (standardized)

Dependent variable	LPPI18		SRI18		WRLURI18	
	OLS	IV	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)	(6)
Gini	-0.030	23.296***	-0.865	5.041**	-1.064	10.045**
	(2.263)	(7.208)	(1.657)	(2.142)	(2.390)	(4.012)
Observations	841	841	841	841	841	841
F statistic		20.710		20.710		20.710
County controls	✓	✓	✓	✓	✓	✓
State fixed effects	✓	✓	✓	✓	✓	✓

A one s.d. $\uparrow$ in the Gini coefficient $\Rightarrow$ A 0.35 standard deviation $\uparrow$ in WRLURI

Implication on Housing Supply

Dependent variable	log(Permits)		$\frac{\text{Permits}}{\text{Population}}$		$\frac{\text{Multifamily permits}}{\text{Population}}$	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Gini	1.689	-16.150**	-0.005	-0.492**	-0.002*	-0.022***
	(1.096)	(6.827)	(0.034)	(0.244)	(0.001)	(0.008)
Observations	6,125	6,125	6,147	6,147	6,147	6,147
F statistic		37.242		37.110		37.110
County controls	✓	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓	✓

A one s.d. $\uparrow$ in the Gini coefficient $\Rightarrow$ Building permits in the following decade $\downarrow$ 58%

Implication on Housing Supply

Dependent variable	log(Permits)		$\frac{\text{Permits}}{\text{Population}}$		$\frac{\text{Multifamily permits}}{\text{Population}}$	
	OLS (1)	IV (2)	OLS (3)	IV (4)	OLS (5)	IV (6)
Gini	1.689	-16.150**	-0.005	-0.492**	-0.002*	-0.022***
	(1.096)	(6.827)	(0.034)	(0.244)	(0.001)	(0.008)
Observations	6,125	6,125	6,147	6,147	6,147	6,147
F statistic		37.242		37.110		37.110
County controls	✓	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓	✓

A one s.d. $\uparrow$ in the Gini coefficient $\Rightarrow$ Building permits in the following decade $\downarrow$ 58%

Implication on Homeownership

Dependent variable	Homeownership rate			
	OLS-all (1)	IV-all (2)	IV-inelastic (3)	IV-elastic (4)
Gini	-0.143*** (0.031)	-0.521** (0.250)	-1.707*** (0.408)	0.344 (0.478)
Observations	9,277	9,277	4,654	4,609
F statistic		36.568	20.954	10.250
County controls	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓

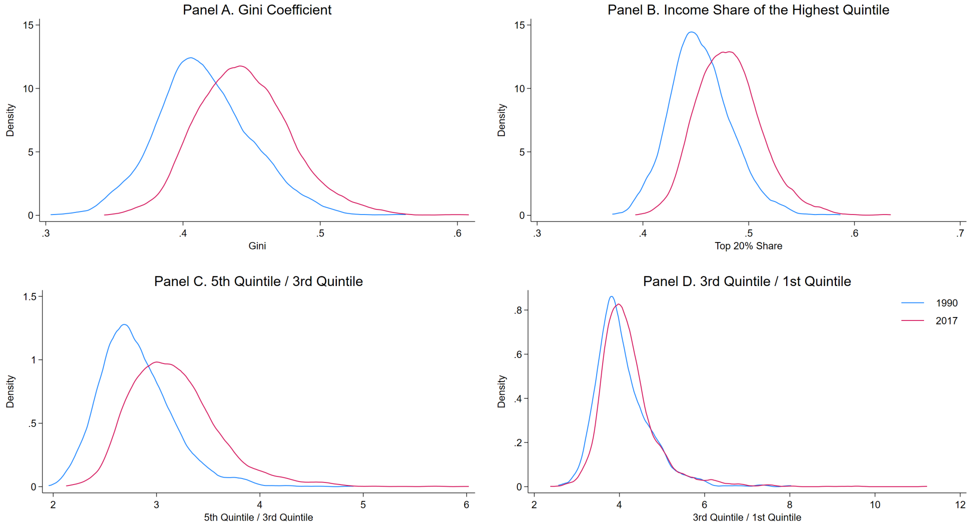
A one s.d. $\uparrow$ in the Gini coefficient $\Rightarrow$ Homeownership rate $\downarrow$ 1.88 pp

▸ Price-Income Ratio

Conclusion

- Income inequality has a positive effect on house prices
- Income inequality is one cause of local housing regulations
- Implications for homeownership and wealth inequality
- Next step: develop a quantitative model

Distribution of Income Inequality



Back

Summary Statistics

Sample	1990	2017	Total
	(1)	(2)	(3)
Gini coefficient	0.415 (0.035)	0.445 (0.034)	0.433 (0.036)
log(Building Permits)	7.847 (1.447)		6.861 (1.940)
log(Population)	11.155 (1.103)	10.561 (1.320)	10.682 (1.268)
log(Median value)	11.053 (0.407)	11.880 (0.440)	11.567 (0.517)
log(Housing units)	10.286 (1.080)	9.813 (1.245)	9.889 (1.209)
Homeownership (%)	0.698 (0.082)	0.715 (0.081)	0.720 (0.080)
log(Mean income)	10.411 (0.196)	11.149 (0.219)	10.878 (0.326)
log(Median income)	10.209 (0.218)	10.874 (0.241)	10.629 (0.322)
Observations	1,439	2,731	9,287

Back

First-Stage: House Prices and Its IV

Dependent variable	log(HPI)		
	(1)	(2)	(3)
log(National HPI) $\times$ Land unavailability	0.001***	0.001***	0.004***
	(0.0003)	(0.0002)	(0.0005)
Observations	9,230	9,230	9,198
County controls		✓	✓
County fixed effects			✓
Year fixed effects			✓

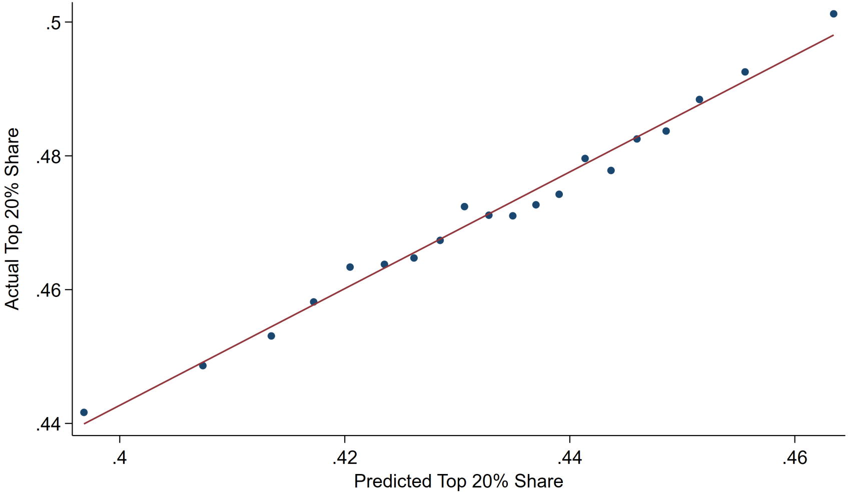
▸ Back

Occupations and OCC1990 Codes

Occupation	OCC1990
Executive, Administrative, and Managerial Occupations	3-22
Management-Related Occupations and Professional Specialty Occupations	23-200
Technicians and Related Support Occupations	203-235
Sales Occupations	243-283
Administrative Support Occupations	303-389
Private Household Occupations	405-407
Protective Service Occupations	415-427
Other Service Occupations	434-469
Farming, Forestry, and Fishing Occupations	473-498
Precision Production, Craft, and Repair Occupations	503-699
Machine Operators, Assemblers, and Inspectors	703-799
Transportation Occupations	803-859
Helpers, Construction and Extractive Occupations	865-889
Military Occupations	905
Unemployed	N.A.

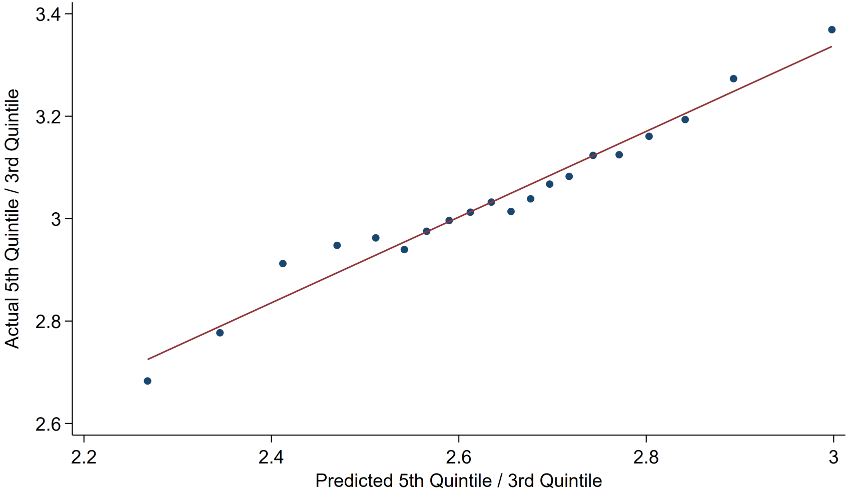
Back

First-Stage: Actual and Synthetic Top 20% Share



Back

First-Stage: Actual and Synthetic $\overline{\text{5th Quintile}}$ / $\overline{\text{3rd Quintile}}$



Back

IV Results: Top 20% Share

Dependent variable	Top 20% share	log(HPI)		
	First-stage	IV-all	IV-inelastic	IV-elastic
	(1)	(2)	(3)	(4)
Predicted top 20% share	0.682***			
	(0.135)			
Top 20% share		9.998***	12.022**	6.817
		(3.478)	(5.155)	(5.004)
Observations	9,277	9,194	4,612	4,568
F statistic		24.474	14.380	6.588
County controls	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓

Back

IV Results: $\frac{\text{5th Quintile}}{\text{3rd Quintile}}$

Dependent variable	$\frac{\text{5th Quintile}}{\text{3rd Quintile}}$		log(HPI)	
	First-stage	IV-all	IV-inelastic	IV-elastic
	(1)	(2)	(3)	(4)
Predicted $\frac{\text{5th Quintile}}{\text{3rd Quintile}}$	0.894***			
	(0.123)			
$\frac{\text{5th Quintile}}{\text{3rd Quintile}}$		0.532***	0.787***	0.278*
		(0.118)	(0.214)	(0.144)
Observations	9,277	9,194	4,612	4,568
F statistic		57.685	25.289	36.008
County controls	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓

Back

IV Results: Excluding 2010 Data

Dependent variable	Gini	log(HPI)			
	First-stage	OLS-all	IV-all	IV-inelastic	IV-elastic
	(1)	(2)	(3)	(4)	(5)
Predicted Gini	1.049***				
	(0.172)				
Gini		-0.403	8.280***	13.477***	3.988
		(0.266)	(2.244)	(4.469)	(2.865)
Observations	6,220	6,183	6,183	3,111	3,061
F statistic			35.807	19.088	12.541
County controls	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓

Back

IV Results: Balanced Panel

Dependent variable	Gini	log(HPI)			
	First-stage	OLS-all	IV-all	IV-inelastic	IV-elastic
	(1)	(2)	(3)	(4)	(5)
Predicted Gini	0.952***				
	(0.162)				
Gini		-0.496*	7.488***	12.477***	3.163
		(0.269)	(2.170)	(4.428)	(2.593)
Observations	5,752	5,731	5,731	2,828	2,883
F statistic			34.212	18.197	10.173
County controls	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓

Back

IV Results: Counties in MSA

Dependent variable	Gini	log(HPI)			
	First-stage	OLS-all	IV-all	IV-inelastic	IV-elastic
	(1)	(2)	(3)	(4)	(5)
Predicted Gini	0.910***				
	(0.158)				
Gini		-0.505**	7.476***	11.577***	3.963
		(0.251)	(2.298)	(4.357)	(2.934)
Observations	6,454	6,433	6,433	3,228	3,187
F statistic			32.271	18.327	8.948
County controls	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓

Back

OLS Results: Following Kösem '23

Dependent variable	log(HPI)			
	(1)	(2)	(3)	(4)
Gini	-1.612***	-0.412**		
	(0.414)	(0.204)		
Top 5% share			-1.936***	-0.714***
			(0.387)	(0.175)
Observations	8,927	8,923	8,927	8,923
County controls	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓
Year fixed effects	✓		✓	
State-year fixed effects		✓		✓

Back

OLS Results: Alternative Measures of Inequality

Dependent variable	log(HPI)				
	(1)	(2)	(3)	(4)	(5)
Gini	-0.593***				
	(0.211)				
Top 5% share		-0.828***			
		(0.213)			
Top 20% share			-0.550**		
			(0.261)		
$\overline{\text{5th Quintile}}$ / $\overline{\text{3rd Quintile}}$				-0.008	
				(0.023)	
$\overline{\text{5th Quintile}}$ / $\overline{\text{1st Quintile}}$					-0.001
					(0.002)
Observations	9,194	9,194	9,194	9,194	9,194
County controls	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓

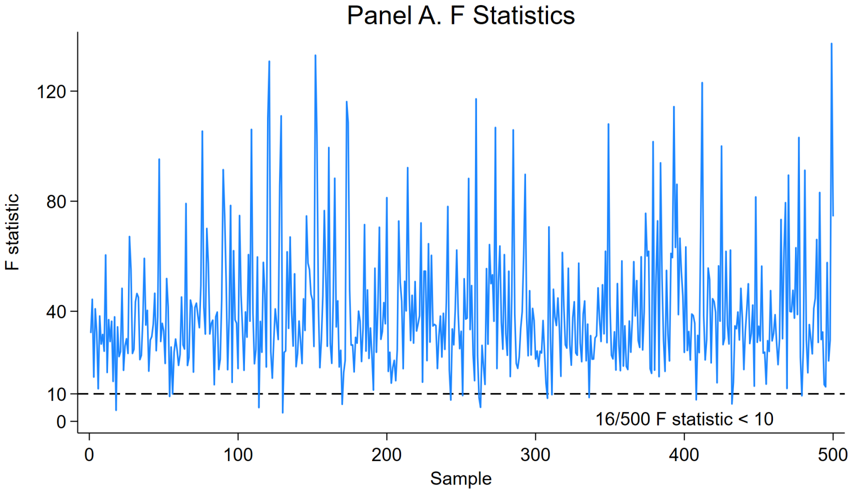
Back

OLS Results: Controlling for Median Income

Dependent variable			log(HPI)		
	(1)	(2)	(3)	(4)	(5)
Gini	1.056***				
	(0.212)				
Top 5% share		0.789***			
		(0.192)			
Top 20% share			1.472***		
			(0.252)		
$\overline{\text{5th Quintile}} \, / \, \overline{\text{3rd Quintile}}$				0.152***	
				(0.022)	
$\overline{\text{5th Quintile}} \, / \, \overline{\text{1st Quintile}}$					0.007***
					(0.002)
Observations	9,194	9,194	9,194	9,194	9,194
County controls	✓	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓	✓

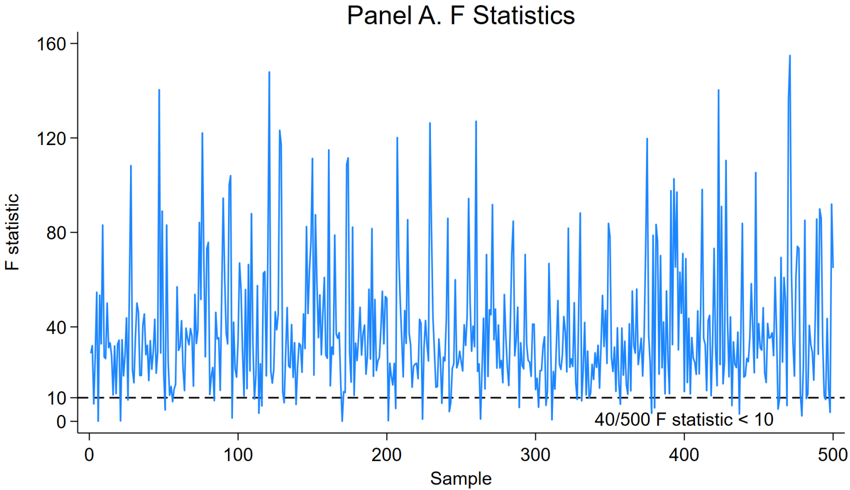
▸ Back

F-Statistics of Random IV (70 Groups)



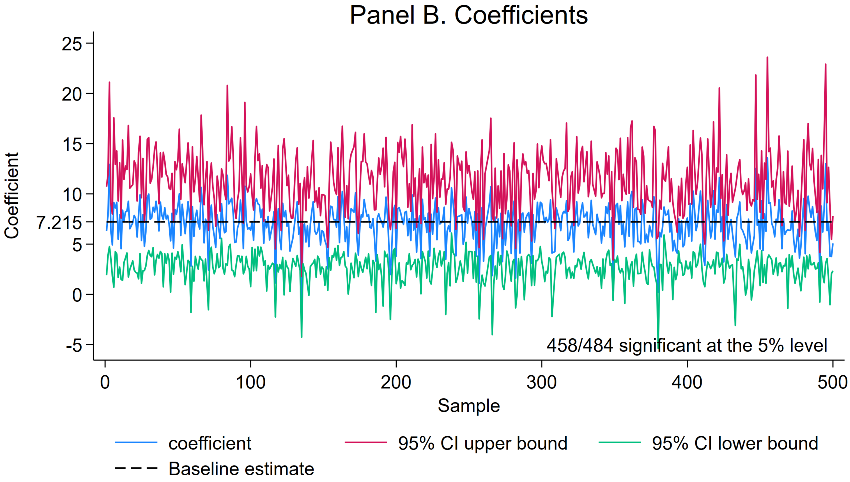
Back

F-Statistics of Random IV (60 Groups)



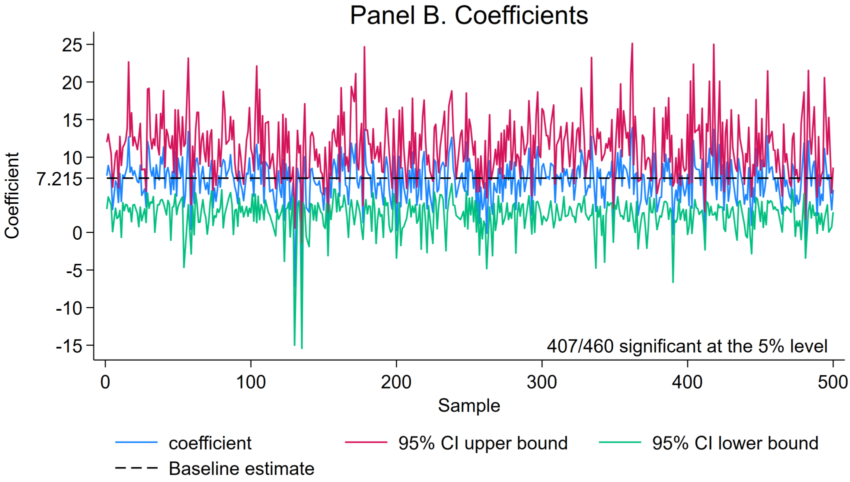
▸ Back

IV Results Using Random IV (70 Groups)



Back

IV Results Using Random IV (60 Groups)



Back

Effect on Demand Side

Dependent variable	Gini	log(Origination)		Investment	
	First-stage	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)	(5)
Predicted Gini	0.926***				
	(0.153)				
Gini		-5.551***	-83.609***	0.323***	6.342***
		(0.571)	(13.978)	(0.082)	(1.215)
Observations	9,277	9,254	9,254	9,264	9,264
F statistic			36.376		36.376
County FE	✓	✓	✓	✓	✓
State-year FE	✓	✓	✓	✓	✓

Back

Reverse Causality: Effect of Housing Stocks on Inequality

Dependent variable	ΔLog(Units)	ΔGini	
	First-stage	OLS	IV
	(1)	(2)	(3)
Land unavailability	0.0004***		
	(0.0001)		
ΔLog(Units)		0.034***	0.197*
		(0.013)	(0.109)
Observations	1,438	1,438	1,438
F statistic			8.771
County controls	✓	✓	✓
State fixed effects	✓	✓	✓

Back

Implication on Affordability

Dependent variable	Price-income ratio			
	OLS-all	IV-all	IV-inelastic	IV-elastic
	(1)	(2)	(3)	(4)
Gini	1.866*	25.490**	30.470*	19.948**
	(1.072)	(10.634)	(15.956)	(8.791)
Observations	9,277	9,277	4,654	4,609
F statistic		36.568	20.954	10.250
County controls	✓	✓	✓	✓
County fixed effects	✓	✓	✓	✓
State-year fixed effects	✓	✓	✓	✓

Back