Equal Prices, Unequal Access

The Effects of National Pricing in the Life Insurance Industry

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- Regulators may try to promote financial inclusion through **pricing restrictions**
  - Examples: interest rate caps, fixed-rate disaster lending, ACA ratings areas
  - **Caveat:** firms may respond by limiting **access** to products

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What are the distributional effects of national pricing?

... across households?
... across locations?
... along each margin?

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- Collect a new dataset linking life insurance companies to **local agents**
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- Build a spatial model of **multi-region** insurers facing heterogeneous **local demand elasticities**
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  - Under national pricing: **lower markups** $\rightarrow$ fewer agents $\rightarrow$ **lower access**
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  - Provide a welfare decomposition that highlights both **pricing** and **access** margin effects
- ◇ Estimate the national pricing equilibrium, compare to the flexible pricing equilibrium
  - Compensating differentials: how much $ to give households to equate welfare to optimal location?

Findings: National Pricing Not Very Effective At Reducing Inequality

- Need to give \$351-\$506/yr to households in poorest decile of CZs under **flexible pricing**
  - $\sim$ 0.41-0.95% of yearly wage
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  - Poorest locations: low-income hh's lose additional \$10/yr, high-income hh's gain \$16/yr
  - Low-income effects dominated by **access** margin
- Complementary place-based policy $\rightarrow$ subsidize revenues in poor locations, tax rich locations
  - Poorest locations: low-income hh's gain \$50/yr, high-income hh's gain \$100/yr
  - Welfare inequality $\downarrow$ by 10-20% depending on policy scale

Literature

- ◇ National/Uniform Pricing

  Finance: Finkelstein & Poterba (2004, 2006), Hurst, Keys, Seru, & Vavra (2016), Fang & Ko (2020), Begley et al (2023)

  Retail: Cavallo, Neiman, & Rigobon (2014), DellaVigna & Gentzkow (2019), Adams & Williams (2019), Anderson, Rebelo, & Wong (2019), Butters, Sacks, & Seo (2022), Daruich & Kozlowski (2023)

  ⋆ **Contribution: endogenous location decisions and access margin welfare effects**

- ◇ Geographic organization of firms

  Jia (2008), Holmes (2011), Ramondo and Rodríguez-Clare (2013), Behrens et al. (2014), Tintelnot (2016), Gaubert (2018), Ziv (2019), Oberfield, Rossi-Hansberg, Sarte, & Trachter (2023), Kleinman (2022), Oberfield, Rossi-Hansberg, Trachter, & Wenning (2023)

  ⋆ **Contribution: effect of pricing restrictions on organization**

- ◇ Financial inclusion

  Buera, Shin, & Kaboski (2011, 2015, 2021), Celeriér & Matray (2019), Beraja, Fuster, Hurst, & Vavra (2019), Cox, Whitten, & Yogo (2022), Lurie & Pearce (2021), Ji, Teng, & Townsend (2022), Brunnermeier, Limodio, & Spadavecchia (2023)

  ⋆ **Contribution: structural approach, life insurance sector**

The Geography of the US Life Insurance Industry

1. Institutional setting
2. Data construction
3. Stylized facts

Institutional Setting

1. **Regulators do not allow life insurance firms to price on geographic identifiers**
   - Can price on: age, gender, health, smoking, + lifestyle activities
   - Cannot price on: geography, income, racial demographics

2. **Life insurance sales come primarily from local insurance agents**
   - 90% of total life insurance sales in 2022 went through agents, only 6% online [LIMRA, 2023]
   - 73% of households in 2016 had purchased life insurance in-person
   - Of those with no insurance, **35%** due to no agent interaction, **50%** due to product complexity

Data Construction

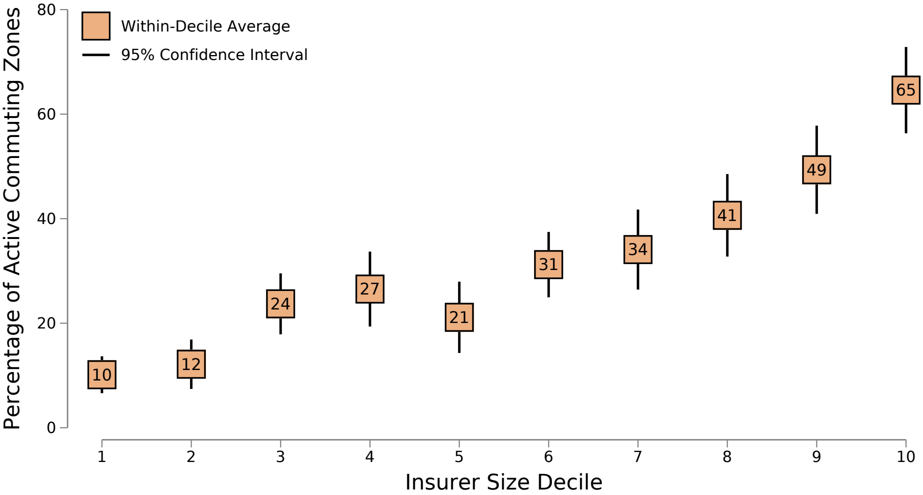
- **Agent Location Data (New!)** – NAIC State-Based Systems
  - 18 states, 280 commuting zones, $\approx$ 30% of the population
  - 210k local agents, >1m agent-insurer pairs
  - Agent business zipcode $\rightarrow$ aggregate to CZ

- **Insurance Prices** – Compulife
  - Life insurance prices used directly by agents
  - Use 10-year term-life premiums for non-smoking 40 year olds in regular health

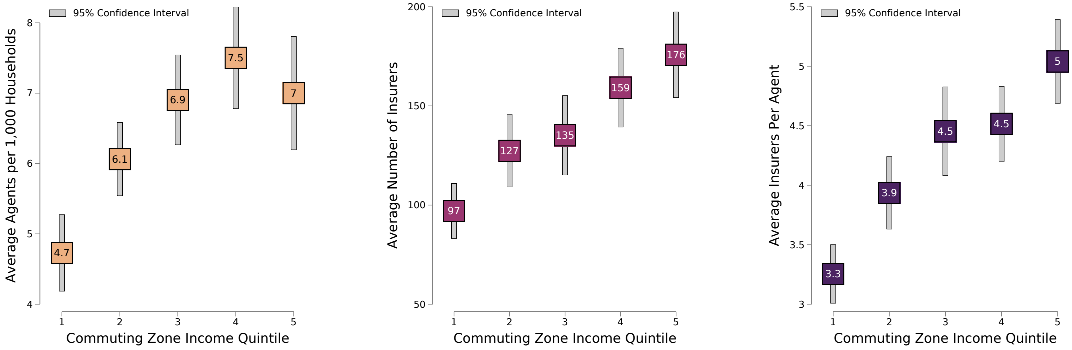
- **Balance Sheet Data** – A.M. Best Financial Suite
  - State-level premiums (sales), liabilities, leverage, ratings, ownership structure

- **Market Fundamentals** – ACS 2016-2020
  - Household population, population by income bracket
  - High-income households = income > $75,000 ($\approx$ 2020 median)

Fact 1: Insurers Are Not Active in Every Commuting Zone



Fact 2: Poor CZs Have Fewer Local Agents and Insurance Options



(a) Agents/1k Households

(b) Active Insurers

(c) Insurers/Agent

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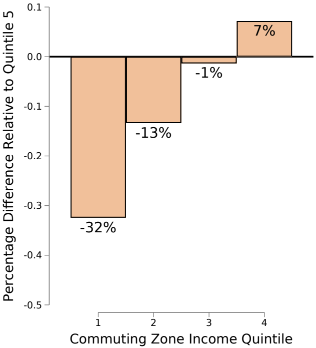

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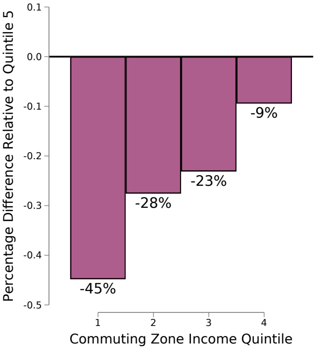
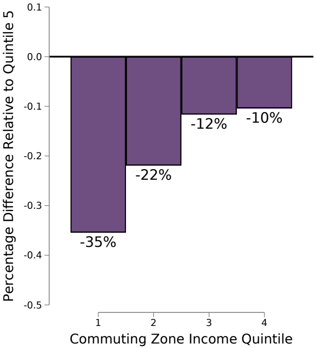
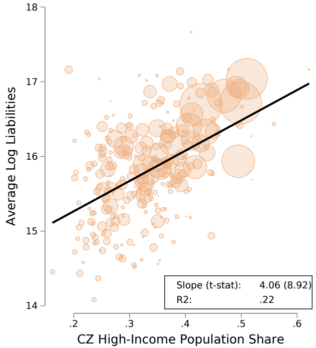


(b) Active Insurers

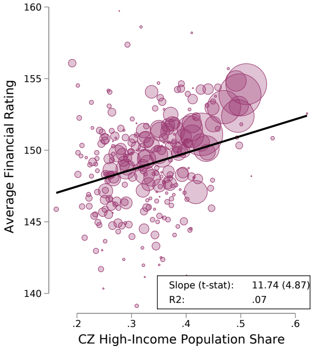


(c) Insurers/Agent

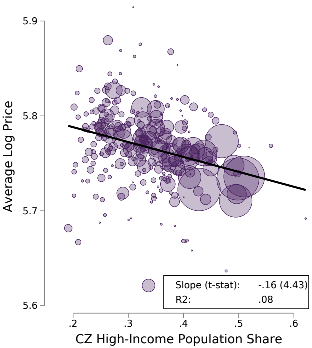
Fact 3: Poor CZs Have Lower Quality Local Insurers on Average



(a) Average Size



(b) Average Rating



(c) Average Log Price

Recap of Facts

1. Insurers are segmented across commuting zones
2. Poorer commuting zones have fewer local insurance options
3. Larger and higher-quality insurers are less active in poor markets

A Spatial Model of Life Insurance Distribution

1. Model Setup
2. Segmentation and spatial sorting
3. Effects of national pricing

Fundamentals

- ◇ **Households** (i)**:** Discrete choice over set of available insurers and outside savings option
  - Two income types: low (ℓ) and high (h) income
  - Funds spent on insurance/savings: $B_\ell < B_h$
- ◇ **Locations** (s)**:** population N_s, high-income population share η_s
- ◇ **Insurers** (j)**:** Hire local sales agents to acquire local customers, set prices

Deriving Household Demand: Discrete Choice

- Household i of type $\boldsymbol{k} \in \{\ell, h\}$ chooses insurer/outside savings option according to

$$u_{is}^{k} = \max_{j \in \mathcal{J}_{is} \cup \{o\}} \underbrace{\log \boldsymbol{\iota_k}}_{\text{value of insurance}} + \underbrace{\log \omega_j}_{\text{insurer quality}} - \underbrace{(\varepsilon_{\boldsymbol{k}} - 1) \log p_{js}}_{\text{distaste for prices}} + \underbrace{\nu_{ij}}_{\text{taste shock}}, \qquad \nu_{ij} \sim \text{EV1}(0,1)$$

- Expositional assumption: $\varepsilon_h > \varepsilon_\ell$ (will verify in estimation)

Deriving Household Demand: Aggregation

- Aggregating within location s, insurer j demand from type k households:

$$Q_{js}^k(p_{js}, \kappa_{js}) = \underbrace{D_{js}^k p_{js}^{-\varepsilon_k}}_{\substack{\text{local demand of all} \\ \text{possible households}}} \times \underbrace{\boldsymbol{\kappa_{js}}}_{\substack{\text{fraction of} \\ \text{households reached}}}$$

- Demand shifter D_{js}^k: local expenditures, preferences, local price index (P_s^k)
- Match probability $\boldsymbol{\kappa_{js}}$: endogenous insurer decision, determines local access

Insurers Reach Households by Hiring Local Agents

- Household-insurer match probability governed by a function:

$$\kappa_{js} \equiv \kappa(\underbrace{\overbrace{\textbf{local agents } a_{js}}^{\text{insurer choice}}}_{(+)} \; ; \; \overbrace{\underbrace{j\text{'s productivity}}_{(+)}, \; \underbrace{s\text{'s population}}_{(-)}}^{\text{model fundamentals}})$$

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Agent Costs:

1. Span of control costs, $C_j(\mathbf{a}_j)$ (managerial cost of employing many agents)
2. Local per-agent hiring costs, f_s (local search costs, office space, cost of leads)

Insurer Profits

$$\Pi_j(\mathcal{P}) = \max_{\mathbf{a}_j, \mathbf{p}_j} \quad \sum_{s \in \mathcal{S}} \Bigg[\underbrace{\overbrace{(p_{js} - \xi_j)}^{\text{local markup}} \Big(Q_s^{\ell}(p_{js}, \kappa_{js}(a_{js})) + Q_s^{h}(p_{js}, \kappa_{js}(a_{js})) \Big)}_{\text{local variable profits}} - \underbrace{f_s a_{js}}_{\substack{\text{hiring}\\ \text{costs}}} \Bigg] - \underbrace{C_j(\mathbf{a}_j)}_{\substack{\text{span of}\\ \text{control}}}$$

$$\text{s.t.} \quad \mathbf{a}_j \geq 0, \; \mathbf{p}_j \in \mathcal{P}$$

- ⋄ Choose vector of prices $\mathbf{p}_j$ and local agents $\mathbf{a}_j$ to maximize profits
- ⋄ Pricing decisions subject to regulatory regime $\mathcal{P}$: national or flexible pricing

Equilibrium

Definition: Industry Equilibrium

Given local fundamentals $\{N_s, \eta_s, f_s\}_{s\in\mathcal{S}}$, *household fundamentals* $\{\iota_k, \varepsilon_k, B_k\}_{k=\ell,h}$, *insurer fundamentals* $\{\theta_j, \omega_j, \xi_j\}$, *and pricing restrictions* $\mathcal{P}$, *an* <u>*industry equilibrium*</u> *is such that*

1. *Households' discrete choice consistent with utility maximization*
2. *Insurers maximize their profits given local price indices,* $\{P_s^h, P_s^\ell\}_s$
3. *Local price indices are consistent with insurers' optimal choices* $\{\boldsymbol{\kappa}_j, \boldsymbol{p}_j\}_j$

How Do Insurers Choose Locations?

◇ Assume $\kappa_{js}(a) = \tilde{\kappa}_s(\theta_j a)$. Optimality implies

$$\underbrace{\Phi_s}_{\substack{\text{local}\\\text{profitability}}} \times \underbrace{\theta_j \tilde{\kappa}_s'(\theta_j a_{js})}_{\substack{\text{marginal household}\\\text{reached}}} \leq \underbrace{f_s}_{\substack{\text{marginal}\\\text{hiring cost}}} + \underbrace{C_j'(\mathbf{a}_j)}_{\substack{\text{marginal span}\\\text{of control cost}}}$$

◇ Optimal number of (productivity-adjusted) agents is

- increasing in local profitability and productivity
- decreasing in hiring and span of control costs

◇ No Inada condition on $\tilde{\kappa}_s(\cdot) \rightarrow a_{js}^* = 0$ in low profitability and high cost locations

How Do Insurers Choose Relative Locations?

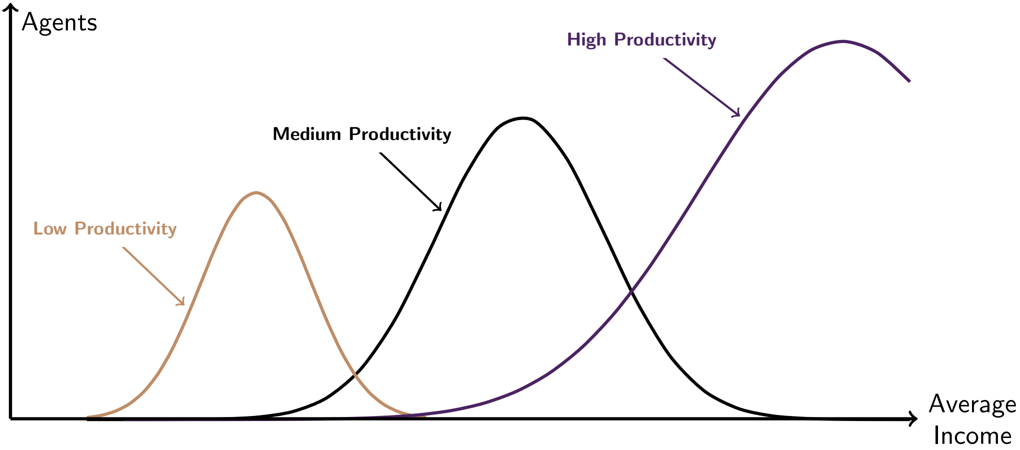
- Two insurers with $\theta_j > \theta_{j'}$, all else equal. Relative optimality condition:

$$\frac{\tilde{\kappa}_s'(\theta_j a_{js})}{\tilde{\kappa}_s'(\theta_{j'} a_{j's})} = \underbrace{\frac{f_s + C_j'(\mathbf{a}_j)}{f_s + C_{j'}'(\mathbf{a}_{j'})}}_{\substack{\text{relative} \\ \text{marginal costs}}} \quad \times \quad \underbrace{\frac{\theta_{j'}}{\theta_j}}_{\substack{\text{relative} \\ \text{productivities}}}$$

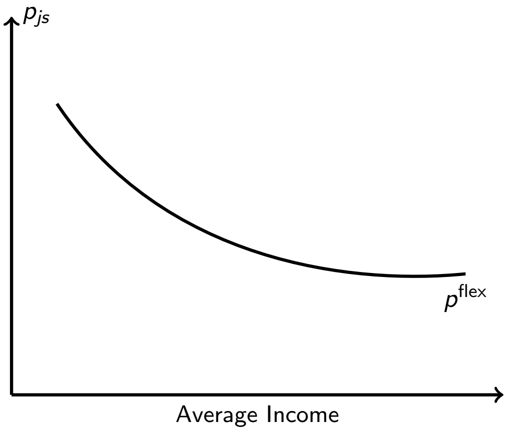
Two Extremes:

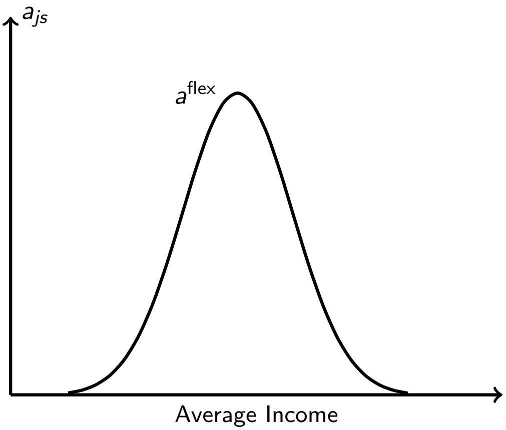
- If $f_s \to 0$, relative agents governed by differences in span of control: $\theta_{j'} a_{j's} > \theta_j a_{js}$
- If $f_s \to \infty$, relative agents governed by differences in productivity: $\theta_{j'} a_{j's} < \theta_j a_{js}$

Proposition 1: Sorting When Hiring Costs Increase With Local Income



Proposition 2: The Effect of National Pricing on Local Agents ($\varepsilon_\ell < \varepsilon_h$)





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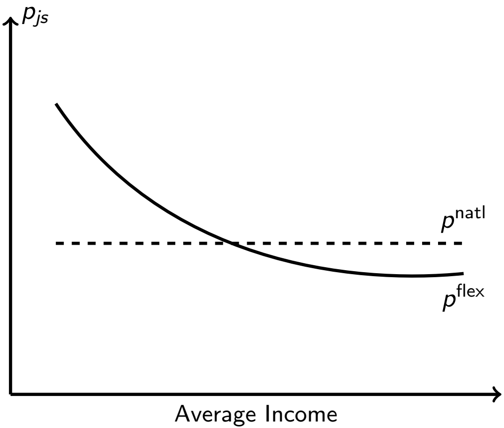

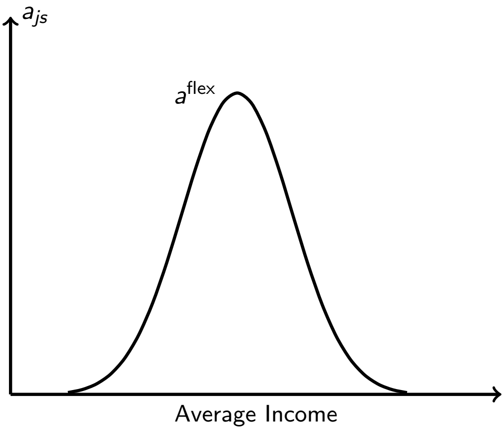

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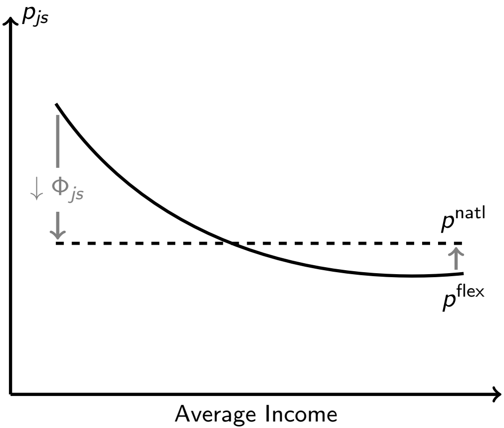

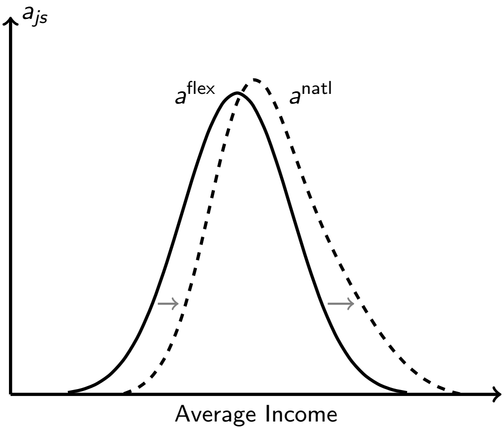

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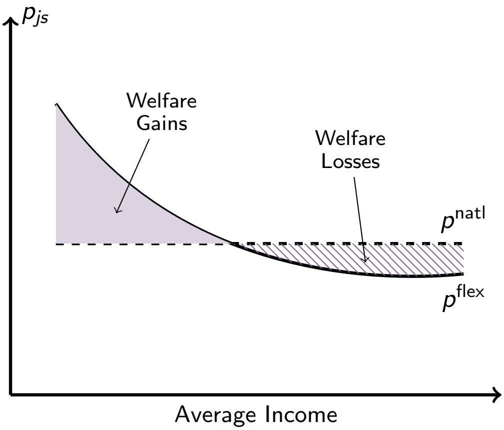
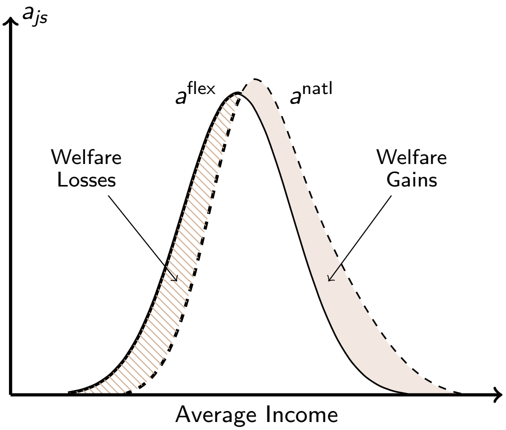




Estimating the National Pricing Equilibrium

1. Price elasticities and insurer quality
2. Insurer parameters (SMM)
3. External validity

Estimating Elasticities: Methodology

- To first order, log sales of firm j in state s are

$$\log S_{js} = \underbrace{\log a_{js} + \log \theta_j}_{\text{match probability}} + \underbrace{\log \omega(\boldsymbol{X}_j)}_{\text{demand components}} - \underbrace{(\varepsilon_\ell - 1)\log p_j}_{\text{baseline elasticity}} - \underbrace{(\varepsilon_h - \varepsilon_\ell)\chi_s^h \log p_j}_{\text{relative elasticity}} + \text{FE}_s$$

- Prices are 10-year term life premiums for 40 y.o.s scaled by actuarial value
  - **Instrument 1:** variable annuity losses and reserve valuation [Koijen Yogo 2022]
  - **Instrument 2:** annuity prices of insurers from 2009 [Hausman Leonard Zona 1994]

- Model demand components as log linear in firm characteristics
  - Characteristics: log liabilities, financial rating, return on equity, stock indicator

Estimation Results: Elasticities are Increasing in Income

	VA Losses IV			Hausman et al IV		
$1-\varepsilon_\ell$	-2.234	-3.154		-1.182	-0.304	
$\varepsilon_\ell-\varepsilon_h$	-2.708^{*}	-2.038^{*}	-1.828^{**}	-2.882^{***}	-2.541^{***}	-2.701^{***}
Agents				✓	✓	✓
θ_j proxy		✓			✓	
Ins-Year FE			✓			✓
Obs	11,326	10,784	12,190	949	949	949
R^2	0.16	0.17	-0.01	0.29	0.75	0.09
F	129.3	146.6	484.7	36.5	56.9	115.6

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. SEs clustered at firm-year level.

Estimating the Remaining Parameters

- ◇ Invert productivities and marginal costs $\{\boldsymbol{\theta}_j, \boldsymbol{\xi}_j\}$ and preferences $\{\iota^h, \iota^\ell\}$
  - Insurer parameters: optimal prices and optimal agent conditions
  - Preferences: aggregate participation rates for each income group
  - Savings to allocate $\{B_k\}$: 1.5% of yearly income
- ◇ Parametrize $\{\{f_s\}, \{C_j(\cdot)\}, \kappa(\cdot)\}$, estimate through SMM
  - target moments from size distribution, sorting, spatial distribution of agents
- ◇ Test the model by computing changes in agents from 2010-2022 with 2010 ACS fundamentals
  - Correlation with the data: 78% (2010), 84% (2022), 78% (changes)

Evaluating Spatial Welfare Inequality

1. Methodology
2. Flexible pricing equilibrium
3. National pricing equilibrium
4. Complementary place-based tax policy

Evaluating Welfare Differences Across Space: Methodology (Totals)

◇ Evaluate spatial heterogeneity in welfare using compensating differentials

◇ Compute savings $\boldsymbol{\hat{B}_{k,cz}}$ needed to equalize welfare between cz and the best off location cz^*:

$$\underbrace{\frac{\boldsymbol{\hat{B}_{k,cz}}}{P^k_{cz}}}_{\substack{\text{average welfare gain}\\ \text{from compensation}}} = \underbrace{\frac{B_k}{P^k_{cz^*}}}_{\substack{\text{optimal}\\ \text{welfare}}} - \underbrace{\frac{B_k}{P^k_{cz}}}_{\substack{\text{average}\\ \text{welfare in } cz}}$$

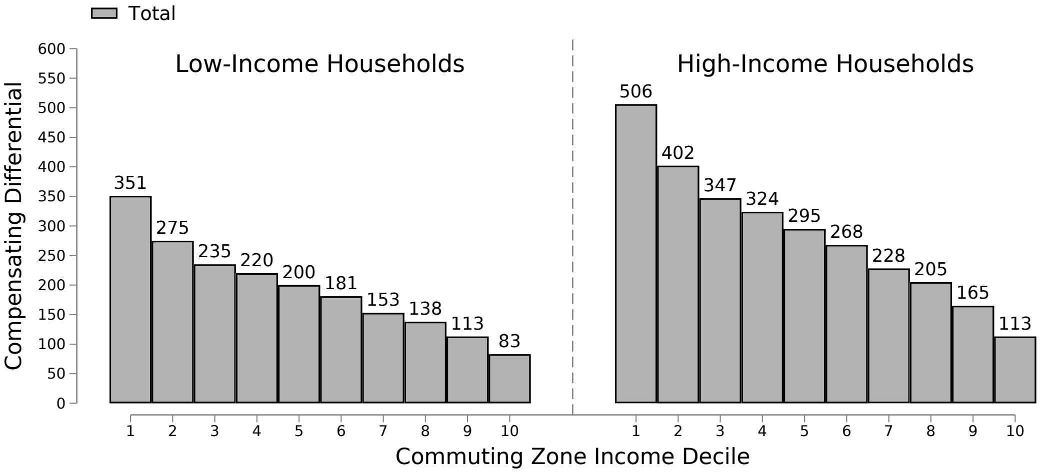
Evaluating Welfare Differences Across Space: Methodology (Margins)

◇ Can further decompose differential into a **pricing** margin ...

$$\frac{\hat{\boldsymbol{B}}^{\text{price}}_{\boldsymbol{k,cz}}}{P^{k,\text{price}}_{cz}} = \underbrace{\frac{B_k}{P^k_{cz^*}} - \frac{B_k}{P^{k,\text{price}}_{cz}}}_{\substack{\text{welfare difference} \\ \text{from prices alone}}}, \qquad P^{k,\text{price}}_{cz} = \left(1 + \iota_k \sum_{j \in \mathcal{J}} \underbrace{\boldsymbol{\omega_j \kappa_{j,cz^*}}}_{\substack{\text{hold fixed} \\ \text{access in } \boldsymbol{cz^*}}} \times \underbrace{\boldsymbol{p^{1-\varepsilon_k}_{j,cz}}}_{\substack{\text{optimal} \\ \text{price in } \boldsymbol{cz}}} \right)^{\frac{1}{1-\varepsilon_k}}$$

... and residual **access** margin, $\hat{\boldsymbol{B}}^{\text{access}}_{\boldsymbol{k,cz}} = \hat{\boldsymbol{B}}_{\boldsymbol{k,cz}} - \hat{\boldsymbol{B}}^{\text{price}}_{\boldsymbol{k,cz}}$

What Drives Spatial Differences in Welfare under Flexible Pricing?



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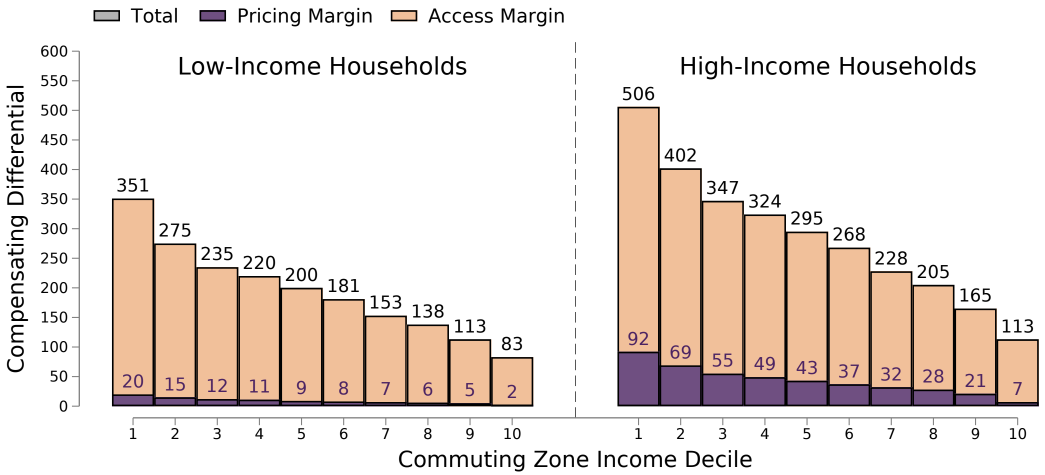

How Does National Pricing Redistribute Across Commuting Zones?

- National pricing is a redistributive policy
  - reallocates surplus from high-income to low-income CZ's on the **pricing margin**
- But **geographic reallocation** of insurers dampens effects of the pricing margin
- Calculate the change in compensating differentials from national pricing

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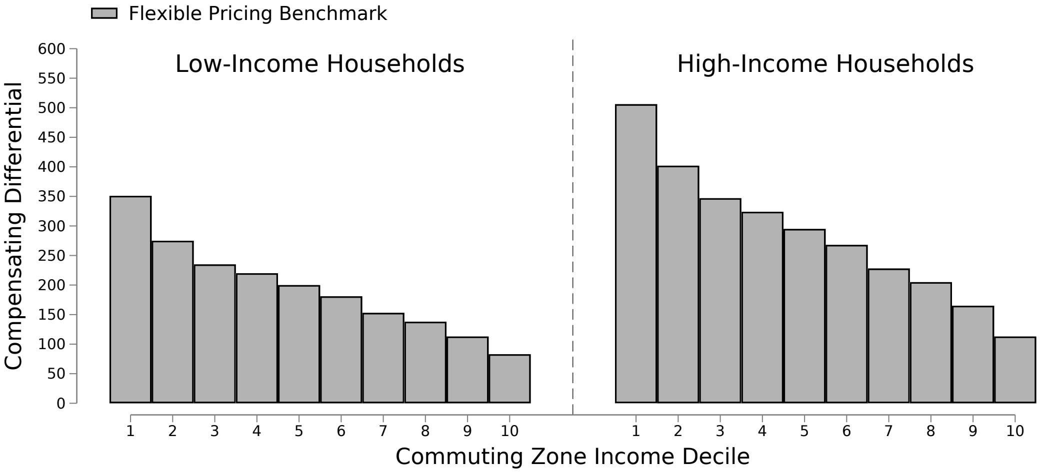

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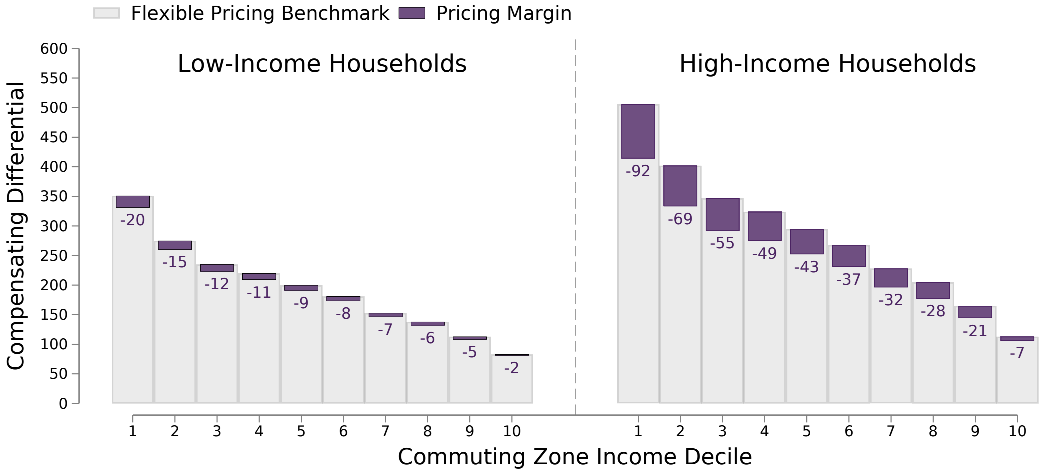

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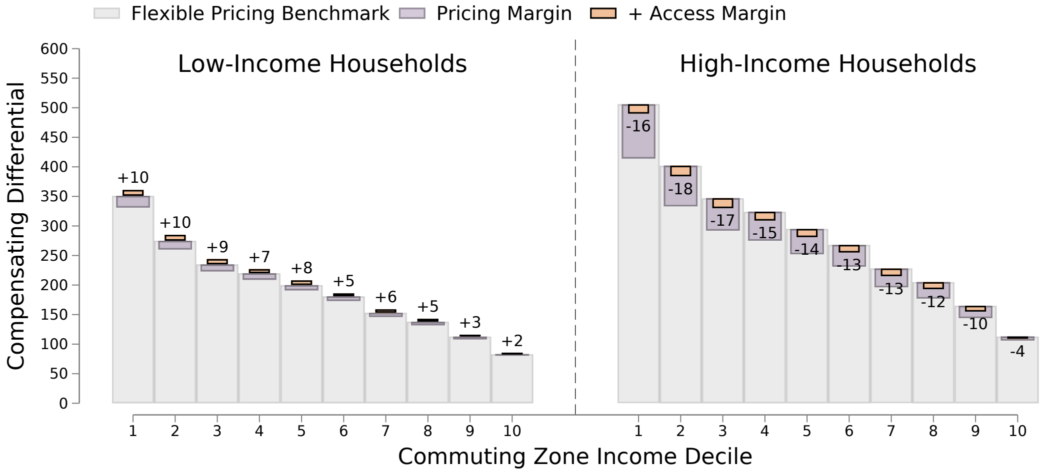

Can Regulators Offset the Access Margin Effects Through Taxes?

- Propose a complementary and revenue-neutral place-based tax policy:
  - reduce premium revenue taxes in low-income commuting zones
  - finance by increasing premium revenue taxes in high-income commuting zones

- Focus on the bottom third of the spatial income distribution, consider two tax schemes:
  1. **no taxes** in poor commuting zones
  2. convert tax rates to **subsidy rates** in poor commuting zones

- Compare to changes in differentials from **national pricing** alone

▸ Policy Details

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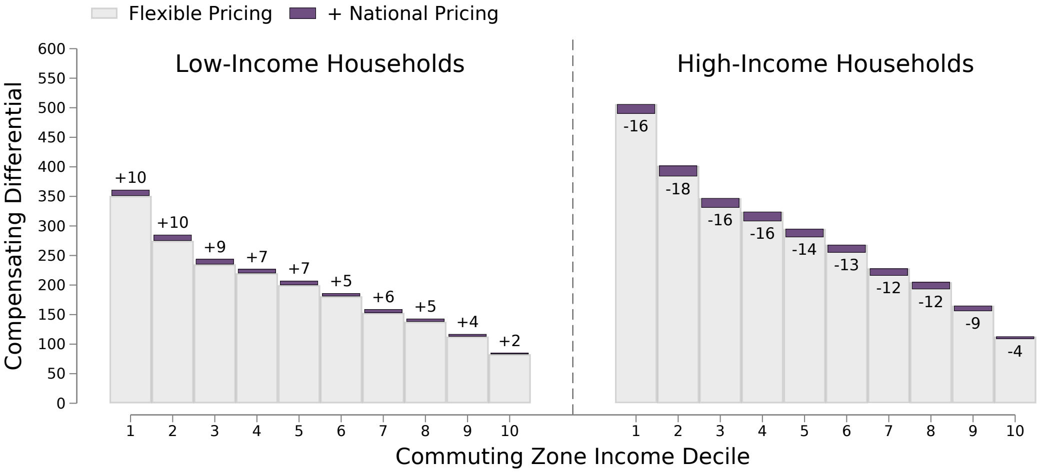

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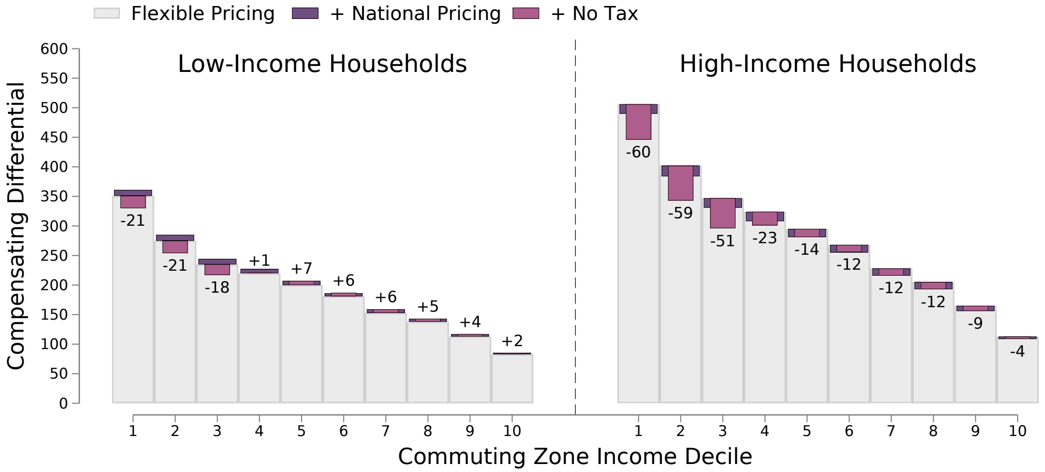

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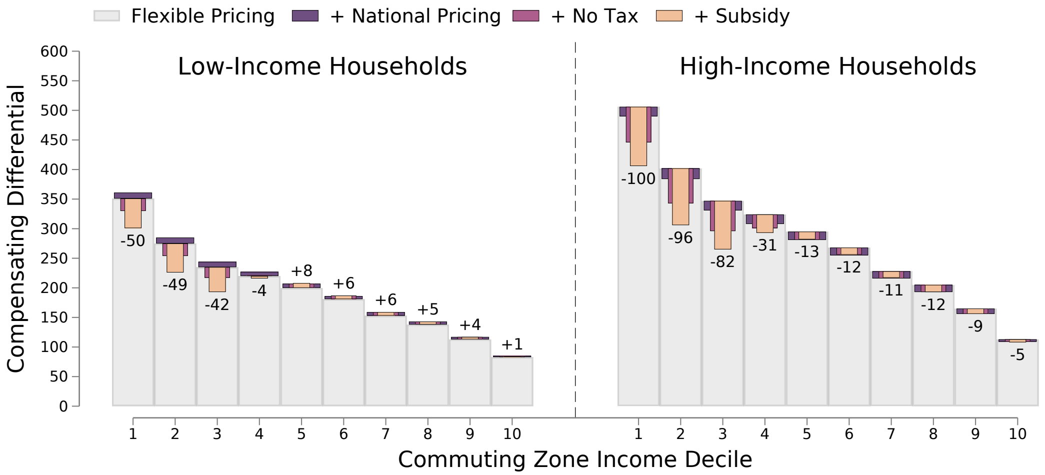

Conclusion

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- $\diamond$ Build and quantify a model of firm location choices $\rightarrow$ assess welfare effects of national pricing
  - lower pricing inequality $\nrightarrow$ lower welfare inequality due to access margin
  - pricing margin relatively unimportant for spatial inequality
- $\diamond$ Complementary place-based policies are useful for targeting access inequality
  - Subsidizing premium revenues in poor places encourages participation through increased access
- $\diamond$ Some steps for future work:
  1. Structural shift toward online and remote access
  2. Test mechanism directly in the UK annuities market

Thank you!

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Appendix

Agents are Important for Local Sales

$$\log(\text{sales}_{js}) = \beta_{\text{ins}} \log(\text{in-state agents})_{js} + \beta_{\text{oos}} \log(\text{out-of-state agents})_{js} + \gamma_j + \gamma_s + e_{js}$$

- If local agents only used for processing and/or digital consulting, expect $\beta_{\text{ins}} = \beta_{\text{oos}}$
- Two functional forms: log and inverse hyperbolic sine (IHS)
  - IHS has similar properties to log, but allows 0's
- Two measures of state-level agents:
  1. Total agents licensed by insurer j in state s
  2. Total fractional agents, adjusts for independent agents selling multiple insurers' products

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Agents are Important for Local Sales

	Log		IHS	
In-State Agents	0.527^{***}	0.467^{***}	0.550^{***}	0.647^{***}
	(0.024)	(0.020)	(0.017)	(0.019)
Out-of-State Agents	0.061^{**}	0.069^{**}	0.067^{***}	0.157^{***}
	(0.030)	(0.028)	(0.018)	(0.019)
Raw Agents	✓	-	✓	-
Fractional Agents	-	✓	-	✓
Obs	4,319	4,319	8,987	8,987
Within R^2	0.17	0.18	0.26	0.27

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroscedasticity-robust SE in parentheses.

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Prices Correlate With Household Characteristics in Firms' Active Markets

- Theory predicts that spatial sorting patterns should matter for prices under national pricing
  - if firms ignore geographic markets, prices should only depend on costs and market power
- Estimate price-sorting correlations conditional on firm characteristics:

$$\log p_j^{am} = \beta^{\text{inc}} \underbrace{\mathbb{E}[\text{income}_s | \boldsymbol{A}_j]}_{\substack{\text{agent-weighted} \\ \text{local income}}} + \beta^{\text{pop}} \underbrace{\mathbb{E}[\text{density}_s | \boldsymbol{A}_j]}_{\substack{\text{agent-weighted} \\ \text{local density}}} + \underbrace{\gamma' \boldsymbol{X}_j}_{\substack{\text{insurer} \\ \text{characteristics}}} + \text{FE}_{am} + \text{error}_j$$

  - Insurer characteristics include firm size, leverage, organization type, and ROE
- Use regression specification to do a variance decomposition of prices
  - even if sorting coefficients significant, how much do they explain relative to other characteristics?

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Prices Correlate With Household Characteristics in Firms' Active Markets

- **Income** is significantly related to prices
  - **density** insignificant across specs.
  - size insig. after controlling for income

	Geog. Only	Firm Only	Both
Income	-0.170^{***}		-0.140^{***}
Density	0.107^{**}		0.094^{**}
Size		-0.102^{***}	-0.056^{**}
ROE		0.020	0.017
Leverage		0.036	0.031
Stock		0.012	-0.013
Obs	731	731	731
Within R^2	0.246	0.169	0.268

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Firm clusters.

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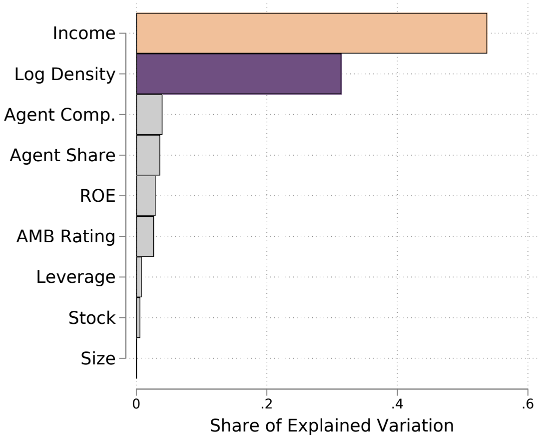
Prices Correlate With Household Characteristics in Firms' Active Markets

- **Income** is significantly related to prices
  - **density** insignificant across specs.
  - size insig. after controlling for income
- Variance decomposition
  - **Income:** 66% of expl. variation
  - **Density:** 18%
  - Firm characteristics: 17%



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Fact 2: Which Commuting Zones Have Local Access to "Good" Insurers?

$$\log(\text{agents}_{j,cz}) = \gamma_j + \gamma_{cz} + \beta^{\boldsymbol{X}}_{\textbf{inc}} X_j \times \log(\text{income}_{cz}) + \beta^{\boldsymbol{X}}_{\textbf{pd}} X_j \times \log(\text{density}_{cz}) + e_{j,cz}$$

- X_j = various measures of insurer "desirability":
  - insurer size
  - financial rating
  - log price
- Regression estimates **relative** allocation of firms along geographic margins (income/density):

$$\beta^X_{\text{inc}} \Bigg[\underbrace{(X_j - X_{j'})\overline{\log(\text{income}_{cz'})}}_{\substack{\text{response of agents to } X \text{ in} \\ \text{high-income commuting zone}}} - \underbrace{(X_j - X_{j'})\underline{\log(\text{income}_{cz})}}_{\substack{\text{response of agents to } X \text{ in} \\ \text{low-income commuting zone}}} \Bigg]$$

▸ Back

Fact 2: Which Commuting Zones Have Local Access to "Good" Insurers?

	Size	Rating	Price
Income	0.123***	0.109***	−0.575***
	(0.007)	(0.008)	(0.059)
Density	0.233***	0.123***	0.082
	(0.008)	(0.009)	(0.067)
Obs	36,471	36,079	10,219
R^2	0.68	0.67	0.75

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Heteroscedasticity-robust SE in parentheses.

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Demand Shifter Construction

- Firm j's demand shifter for households of type k in location s is

$$D_{js}^k = \underbrace{\iota_k}_{\text{taste for insurance}} \times \underbrace{\omega_j}_{\text{quality of insurer } j} \times \underbrace{B_k}_{\text{expenditures per household}} \times \underbrace{\eta_s^k N_s}_{\text{total number of households}} \times \underbrace{(P_s^k)^{\varepsilon_k - 1}}_{\text{local price index}}$$

- Local price index depends on prices p_{js}, local access κ_{js}, and insurer quality ω_j:

$$P_s^k = \left(\underbrace{1}_{\text{outside option}} + \sum_{j \in \mathcal{J}} \underbrace{\omega_j}_{\text{quality}} \times \underbrace{\kappa_{js}}_{\text{access}} \times \underbrace{p_{js}^{1-\varepsilon_k}}_{\text{prices}} \right)^{\frac{1}{1-\varepsilon_k}}$$

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Spatial Sorting: A Formal Result

Proposition: Single-Crossing Condition

Consider two insurers with $\theta_j > \theta_{j'}$. Then there exists a hiring cost threshold such that $A_{js} > A_{j's}$ above the threshold and $A_{js} < A_{j's}$ below the threshold. Further:

- *under flexible pricing, this threshold is unique*
- *under national pricing, this threshold is unique conditional on market income and size*

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Productivity and Span of Control Drive Sorting: An Illustration

- Let $A_{js} \equiv \theta_j a_{js}$ and assume $\kappa_{js} = 1 - \exp(-\theta_j a_{js}/N_s^\alpha)$ (quantitative functional form)

- Suppose $\theta_j > \theta_{j'}$. Can write difference in optimal number of agents as

$$A^*_{js} - A^*_{j's} \;\propto\; \log\left(\frac{f_s/\theta_{j'} + C'_{j'}}{f_s/\theta_j + C'_j}\right) \rightarrow \begin{cases} -\log\left(\dfrac{C'_j}{C'_{j'}}\right) < 0 & \text{as } f_s \to 0 \\ \log\left(\dfrac{\theta_j}{\theta_{j'}}\right) > 0 & \text{as } f_s \to \infty \end{cases}$$

- Monotonicity in f_s → spatial sorting along hiring costs
  - **Connecting to data:** f_s increasing in η_s^h → productive insurers more active in rich locations

▸ Back

Sorting Matters for Prices Under Uniform Pricing

- Optimal prices for a given regulatory regime $\mathcal{P}$ satisfy

$$p_{js}^{*} = \left(\frac{\zeta_{js}}{\zeta_{js}-1}\right)\xi, \qquad \zeta_{js} = \begin{cases} \delta_{js}^{\mathrm{w}}\varepsilon_h + (1-\delta_{js}^{\mathrm{w}})\varepsilon_\ell, & \text{if } \mathcal{P} = \mathcal{P}^{\mathrm{flex}} \\ \sum_{s\in\mathcal{S}} \underbrace{\delta_{js}^{\mathrm{b}}}_{\substack{\text{across-market} \\ \text{sales share}}} \times \left(\underbrace{\delta_{js}^{\mathrm{w}}\varepsilon_h + (1-\delta_{js}^{\mathrm{w}})\varepsilon_\ell}_{\substack{\text{within-firm-market} \\ \text{weighted elasticity}}}\right), & \text{if } \mathcal{P} = \mathcal{P}^{\mathrm{natl}} \end{cases}$$

▸ Back (Sorting) ▸ Back (National Pricing)

Welfare Decomposition

- Can write log difference in welfare across regimes as

$$\log \mathbb{W}_s^{k,\text{natl}} - \log \mathbb{W}_s^{k,\text{flex}} = \log P_s^{k,\text{flex}} - \log P_s^{k,\text{natl}}$$

- To first order, this becomes

$$\Delta \log \mathbb{W}_s^k \approx \frac{\iota_k}{\varepsilon_k - 1}\left[\underbrace{\sum_{j\in\mathcal{J}} \kappa_{js}^{\text{flex}}\left((p_j^{\text{natl}})^{1-\varepsilon_k} - (p_{js}^{\text{flex}})^{1-\varepsilon_k}\right)}_{\text{welfare effect of price changes}} + \underbrace{\sum_{j\in\mathcal{J}}\left(\kappa_{js}^{\text{natl}} - \kappa_{js}^{\text{flex}}\right)(p_j^{\text{natl}})^{1-\varepsilon_k}}_{\text{welfare effects of access changes}}\right]$$

▸ Back

The Effect of National Pricing on Agent Locations

Proposition: Geographic Response to National Pricing

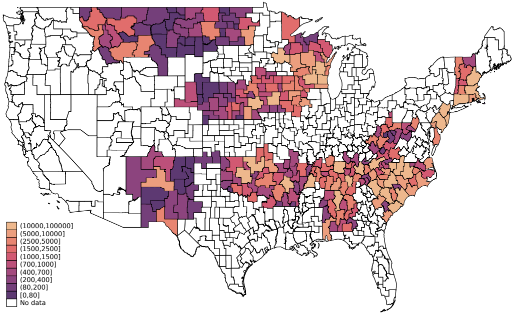
Suppose $\boldsymbol{\iota} \to \infty$, $\boldsymbol{\theta} \to \theta$, and f_s is solely a function of market size, $f_s = f(N_s)$. Then there exists a unique local income threshold schedule $\eta^*(N)$ under national pricing such that:

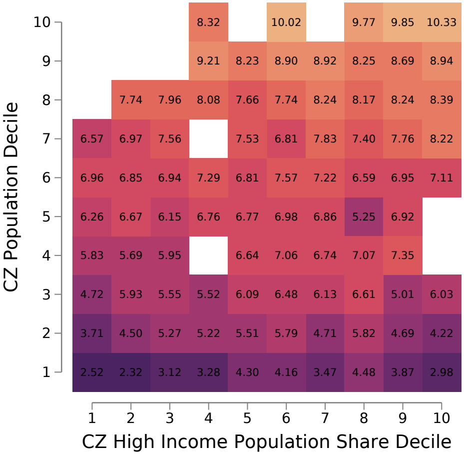
- *below the cutoff, insurers reduce their agents relative to flexible pricing*
- *above the threshold, insurers increase their agents relative to flexible pricing*

◇ National pricing affects local profitability through equilibrium markups

▸ Back

The Spatial Distribution of Life Insurance Agents





Above: agents across US commuting zones

Right: log agents by CZ pop. and income

▸ Back

Derivation of Sales Share Approximation

◇ True sales share of firm j in state s is $\sigma_{js} = \chi_s \sigma_{js}^h + (1 - \chi_s)\sigma_{js}^\ell$

- Can't directly take logs
- Solution: f.o. approximation around $\sigma_{js}^h / \sigma_{js}^\ell \approx 1$

◇ Imposing the approximation gives a **log-linear** structure:

$$\log \sigma_{js} \approx \underbrace{\log \sigma_{os} - \mathbb{E}_s[O^k] - \alpha \log N_s}_{\text{absorb in fixed effect, FE}_s} + \log a_{js} + \log \theta_j + \log \omega_j - (\varepsilon_\ell - 1) \log p_j + (\varepsilon_\ell - \varepsilon_h)\chi_s \log p_j$$

▸ Back

Actuarial Value Definition

- Actuarial (fair) value of a life insurance policy is expected payout for an insurer that uses premium revenues to invest in a portfolio of treasuries:

$$V^{agm} = \left(1 + \sum_{k=1}^{m-1} R^{-k}(k) \prod_{\ell}^{k-1} \rho^g_{a+\ell}\right)^{-1} \left(\sum_{k=2}^{m} R^{-k}(k) \prod_{\ell=0}^{k-2} \rho^g_{a+\ell}(1 - \rho^g_{a+k-1})\right)$$

  - R(k) is gross return on a treasury with maturity k
  - $\rho^g_{a+\ell}$ is lapsation-adjusted (5%) mortality rate of household age $a + \ell$ of gender g

- V captures value of investing to the household → model consistent to scale prices by V

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Agent Time Series

- ◇ Agent data is a snapshot of August 2022, the time of data collection
  - can see when **current** agents became licensed to each insurer
  - do not observe agents that **exited** prior to Aug. 2022
- ◇ Specification uses state-year fixed effects $\rightarrow$ if measurement error scales observed agents over time to same degree across firms, not an issue since error will be absorbed in fixed effects
- ◇ k-period auto correlation is about 58% for 2011, increasing up to 2022

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Details on Annuity Price Instrument

- ◇ Data are collected from Annuity Shopper hosted by Immediate Annuities
  - Pull from July issues each year to correspond to the June quotes from LI pricing data
- ◇ Report a range of annuity prices for men and women aged 50-85 in 5-year increments
  - Estimation uses 50, 55, 60, 65, 70 year olds, averaged across genders
- ◇ Sample is relatively small, only about 15-20 companies per issue
  - only 8-10 firms remain when matched with Compulife prices

▸ Back

Details on VA Losses Instrument

- Instrument is based on the shadow cost of capital concept embodied in Koijen-Yogo 2016, 2022
  - Statutory capital constraints generate shadow costs that transmit into prices
  - KY2022 $\rightarrow$ reserve valuation $\uparrow$, shadow costs $\uparrow$
- Growing literature on how losses across divisions within insurance companies/groups spillover to prices
  - Logic: high shadow costs of capital $\rightarrow$ accumulate short maturity premiums to boost capital
  - Extends to P&C insurance [e.g. Ge 2023 JF]
- First-stage estimates confirm the mechanism: VA losses negatively related to short-term life insurance prices
  - F stat very small for 20- and 30-year policies

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Full Estimation Results

	Variable Annuity Losses			*Annuity Prices*		
	(1)	(2)	(3)	(4)	(5)	(6)
Log Price	−4.338	−4.533		−1.182	−0.304	
	(0.097)	(0.061)		(0.446)	(0.542)	
Log Price × $\tilde{\chi}_s$	−2.708	−2.038	−1.828	−2.882	−2.541	−2.701
	(0.052)	(0.056)	(0.032)	(0.000)	(0.000)	(0.000)
Size	0.809	0.686		0.375	0.427	
	(0.000)	(0.000)		(0.022)	(0.000)	
Rating	−1.420	−0.295		−1.703	−5.507	
	(0.431)	(0.845)		(0.582)	(0.000)	
Stock	−1.399	−0.771		0.583	0.737	
	(0.213)	(0.484)		(0.193)	(0.000)	
ROE	−1.149	−1.042		−0.308	−1.356	
	(0.006)	(0.026)		(0.852)	(0.031)	
Demand Controls	✓	✓		✓	✓	
Productivity Proxy		✓			✓	
Firm-Year FE			✓			✓
Agents				✓	✓	✓
Obs	11326	10784	12190	949	949	949
Within R^2	0.28	0.31	-0.01	0.294	0.75	0.09
F	105.0	111.4	484.7	36.5	56.9	115.6

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Estimation Results with Racial Categories

	Variable Annuity Losses			*Annuity Prices*		
	(1)	(2)	(3)	(4)	(5)	(6)
Low Inc × White	−2.903	−3.172		−2.687	−1.783	
	(0.226)	(0.139)		(0.086)	(0.000)	
High Inc × White	−4.362	−2.038	−3.175	−1.487	−1.374	−1.489
	(0.026)	(0.017)	(0.004)	(0.001)	(0.000)	(0.000)
Low Inc × Non-White	−3.251	−3.069	−2.207	2.551	2.505	2.532
	(0.049)	(0.037)	(0.012)	(0.000)	(0.000)	(0.000)
High Inc × Non-White	−4.163	−3.267	−2.652	−1.168	−0.607	−0.786
	(0.032)	(0.021)	(0.012)	(0.137)	(0.367)	(0.261)
Demand Controls	✓	✓		✓	✓	
Productivity Proxy		✓			✓	
Firm-Year FE			✓			✓
Agents				✓	✓	✓
Obs	11561	11006	12443	949	949	949
Within R^2	0.13	0.15	-0.06	0.29	0.75	0.09
F	65.8	74.4	164.3	18.0	26.1	35.2

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Estimation Results: No Instrument

	(1)	(2)	(3)	(4)	(5)
Price	-0.377^{**}	-0.403^{*}	-0.385	-0.436^{**}	-0.572^{*}
Price $\times\chi_s$	$\mathbf{-0.898^{***}}$	$\mathbf{-0.856^{***}}$	$\mathbf{-0.654^{***}}$	$\mathbf{-0.880^{***}}$	$\mathbf{-0.678^{***}}$
Size	0.322^{***}	0.339^{***}	0.892^{***}	0.280^{***}	0.843^{***}
ROE	-0.280	-0.321	-0.640^{**}	-0.201	-0.173
Stock	-0.296	-0.265	0.330	-0.302^{**}	0.293
Rating	2.131^{***}	1.690^{***}	1.657^{***}	2.698^{***}	3.011^{***}
Leverage	-1.563^{***}	-1.622^{***}	-6.208^{***}	-1.070	-5.739^{***}
Agents	Y	Y	N	Y	N
Years	2007-2018	2007-2015	2007-2015	2011-2018	2011-2018
Obs	11892	8825	27519	8006	24339
R^2	0.609	0.597	0.522	0.618	0.540

Note: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$. SEs clustered at firm-year level.

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Model Inversion: Productivities, Marginal Costs, and Outside Options

◇ Marginal costs $\{\xi_j\}$ can be inverted from the optimal pricing condition:

$$\xi_j = \left(1 - \frac{1}{\zeta_j}\right)\hat{p}_j, \qquad \zeta_j = \sum_{s \in \mathcal{S}} \underbrace{\delta_{js}}_{\substack{\text{between-mkt} \\ \text{sales share}}} \times \underbrace{[\chi_{js}\hat{\varepsilon}_h + (1 - \chi_{js})\hat{\varepsilon}_\ell]}_{\text{local elasticity}}$$

- Estimate commuting-zone-level sales using residual demand
- Construct across-market sales shares for each firm
- Recover firm-level elasticity and back out marginal costs

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Model Inversion: Productivities, Marginal Costs, and Outside Options

- Marginal costs $\{\xi_j\}$ can be inverted from the optimal pricing condition:
- Productivities $\{\theta_j\}$ can be inverted from optimal agent conditions:

$$\hat{S}_j = \zeta_j \sum_{s \in \mathcal{S}} \Big(f_s + C'(\hat{\boldsymbol{a}}_j, \theta_j) \Big) N_s^{\alpha} \left(\frac{\kappa_{js}(\hat{a}_{js}, \theta_j)}{1 - \kappa_{js}(\hat{a}_{js}, \theta_j)} \right)$$

  - Use agent data, observed sales, and guess of model parameters
  - Re-estimate marginal costs with new productivities, solve fixed point

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Model Inversion: Productivities, Marginal Costs, and Outside Options

- Marginal costs $\{\xi_j\}$ can be inverted from the optimal pricing condition:
- Productivities $\{\theta_j\}$ can be inverted from optimal agent conditions:
- Outside option values $\{O^h, O^\ell\}$ set to rationalize participation rates across household types:

$$\hat{\sigma}_o^k = \sum_{s \in \mathcal{S}} \left(\frac{E_s^k}{\sum_{s'} E_{s'}^k} \right) \sigma_{os}^k(O^k)$$

  - High-income participation: 59.7%
  - Low-income participation: 37.4%

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Indirect Inference: Costs and Market Penetration

$$f_s = \tau_0 N_s^{\tau_1} \eta_s^{\tau_2}$$

- Parameters τ_0, τ_1, τ_2 determine costs across locations
  - → use to target **top 20% firm sales (72.9%)** across firms and **allocation of agents** across CZs

$$\log \frac{\mathbb{E}[a_c \mid N_c \text{ in top q\%}]}{\mathbb{E}[a_c \mid N_c \text{ in bot q\%}]} = \beta_0 + \beta_1(50 - q) + \text{error}_q, \qquad q = 50, 45, \ldots, 5$$

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Indirect Inference: Costs and Market Penetration

$$f_s = \tau_0 N_s^{\tau_1} \eta_s^{\tau_2}, \quad C(\bar{A}_j) = \frac{\gamma_0}{\gamma_1} \left(\sum_s A_{js} \right)^{\gamma_1}$$

- Parameters τ_0, τ_1, τ_2 determine costs across locations
  - → use to target **top 20% firm sales (72.9%)** across firms and **allocation of agents** across CZs
- Parameters γ_0 and γ_1 determine costs across firms
  - → use to target **spatial sorting patterns**

$$\sum_{j \in \mathcal{J}} \left(\frac{a_{jc}}{\sum_{j'} a_{j'c}} \right) \log \omega_j = \beta_0^{AS} + \beta_1^{AS} \log \eta_c + \text{error}_c$$

$$\sum_{c \in \mathcal{C}} \left(\frac{a_{jc}}{\sum_{c'} a_{jc'}} \right) \log \eta_c = \beta_0^{RS} + \beta_1^{RS} \log \omega_j + \text{error}_j$$

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Indirect Inference: Costs and Market Penetration

$$f_s = \tau_0 N_s^{\tau_1} \eta_s^{\tau_2}, \quad C(\bar{A}_j) = \frac{\gamma_0}{\gamma_1} \left(\sum_s A_{js} \right)^{\gamma_1}, \quad \kappa_{js}(A_{js}) = 1 - \exp\left(\theta_j A_{js} / N_s^{\alpha} \right)$$

- Parameters τ_0, τ_1, τ_2 determine costs across locations
  - → use to target **top 20% firm sales (72.9%)** across firms and **allocation of agents** across CZs
- Parameters γ_0 and γ_1 determine costs across firms
  - → use to target **spatial sorting patterns**
- Market penetration size penalty α → **average # of agent-insurer pairs (3982)** across CZs

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Indirect Inference: Costs and Market Penetration

$$f_s = \tau_0 N_s^{\tau_1} \eta_s^{\tau_2}, \quad C(\bar{A}_j) = \frac{\gamma_0}{\gamma_1}\left(\sum_s A_{js}\right)^{\gamma_1}, \quad \kappa_{js}(A_{js}) = 1 - \exp\left(\theta_j A_{js}/N_s^{\alpha}\right)$$

- ◇ Parameters τ_0, τ_1, τ_2 determine costs across locations
  - → use to target **top 20% firm sales (72.9%)** across firms and **allocation of agents** across CZs
- ◇ Parameters γ_0 and γ_1 determine costs across firms
  - → use to target **spatial sorting patterns**
- ◇ Market penetration size penalty α → **average # of agent-insurer pairs (3982)** across CZs

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Internal Calibration: Methodology

Guess ψ_n

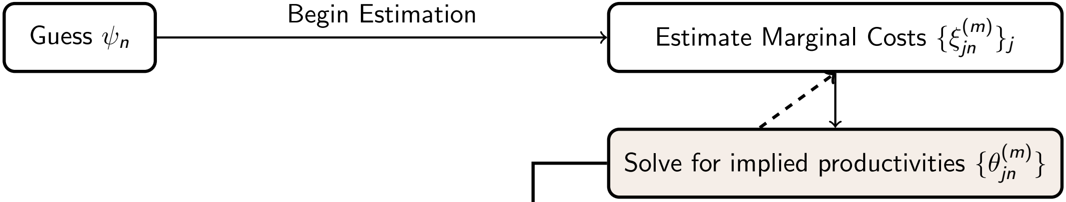
Internal Calibration: Methodology

Guess ψ_n → Begin Estimation → Estimate Marginal Costs $\{\xi_{jn}^{(m)}\}_j$

$$\xi_{jn}^{(m)} = \left(1 - \frac{1}{\zeta_{jn}^{(m)}}\right)\hat{p}_j, \qquad \zeta_{jn}^{(m)} = \sum_{s \in \mathcal{S}} \underbrace{\delta_{jsn}^{(m)}}_{\text{between-mkt sales share}} \times \underbrace{[\chi_{jsn}^{(m)}\hat{\varepsilon}_h + (1-\chi_{jsn}^{(m)})\hat{\varepsilon}_\ell]}_{\text{local elasticity}}$$

- ◇ Estimate commuting-zone-level sales using residual demand
- ◇ Construct across-market sales shares for each firm
- ◇ Recover firm-level elasticity and back out marginal costs

Internal Calibration: Methodology

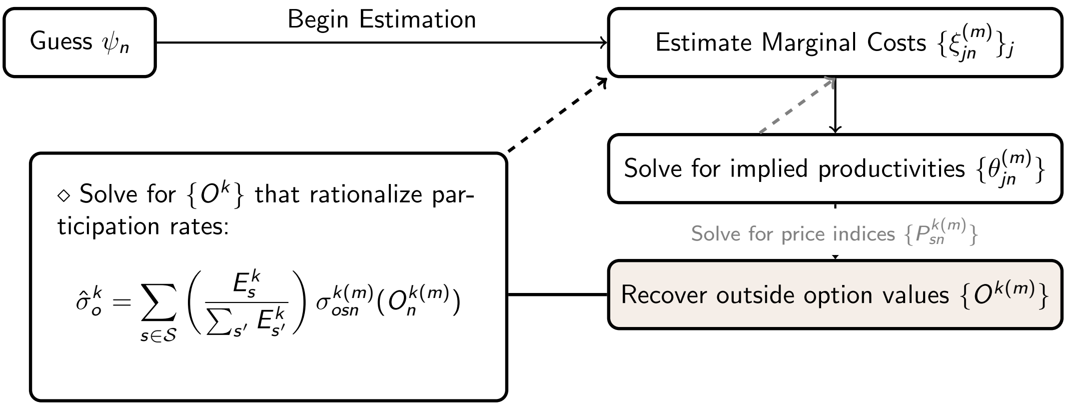


- ◇ Use agent data, observed sales, and ψ_n in FOC:

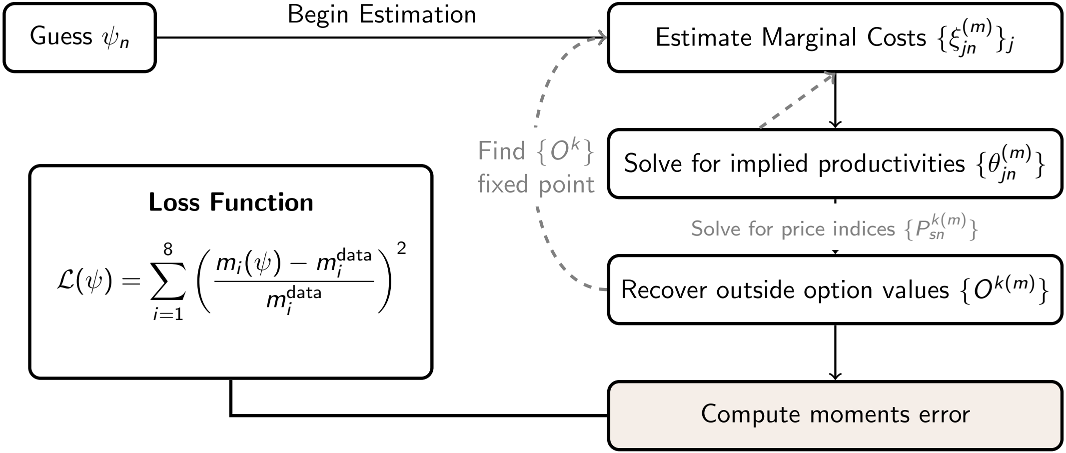
$$\hat{S}_j = \zeta_{jn}^{(m)} \sum_{s \in \mathcal{S}} \Big(f_{sn} + \lambda_{jn}(\theta_{jn}^{(m)}) \Big) N_s^{\alpha_n} \left(\frac{\kappa_{jsn}(\hat{a}_{js}, \theta_{jn}^{(m)})}{1 - \kappa_{jsn}(\hat{a}_{js}, \theta_{jn}^{(m)})} \right)$$

- ◇ Re-estimate marginal costs with new productivities, solve fixed point

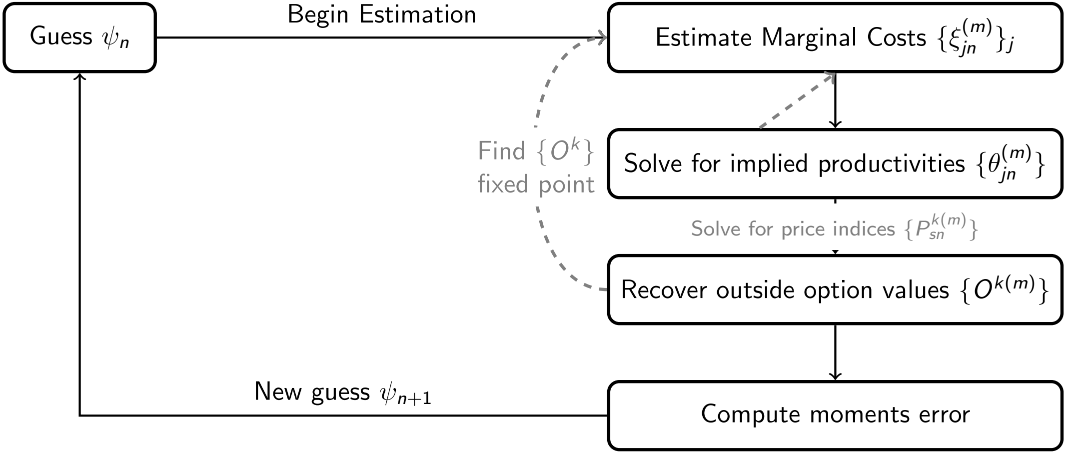
Internal Calibration: Methodology



Internal Calibration: Methodology



Internal Calibration: Methodology



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Internal Calibration: Results

Moment Group	Parameter	Value	Moment	Data	Model
Sorting	γ_0	0.003	relative sorting: β_1^{RS}	0.019	0.016
	γ_1	2.032	absolute sorting: β_1^{AS}	0.781	0.938
	τ_1	0.815	relative agents: β_0	2.206	1.901
	τ_2	-0.785	relative agents: β_1	0.096	0.042
Size	τ_0	0.112	top 20% share	0.729	0.640
	α	0.618	agent-firms per CZ	3982	5794
Participation	O_h	1.995	high-income part.	0.597	0.597
	O_ℓ	10.42	low-income part.	0.374	0.374

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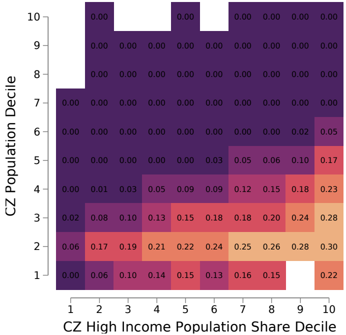
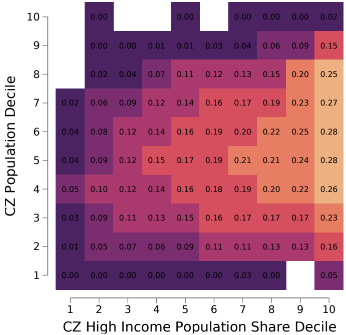
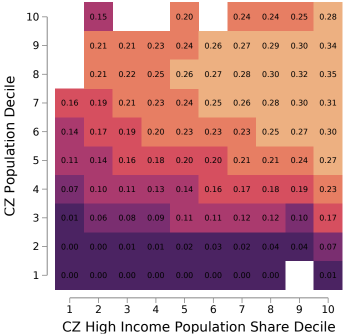
Sorting in the Estimated Model: Market Penetration



(a) Small Firms (4)



(b) Medium Firms (7)



(c) Large Firms (10)

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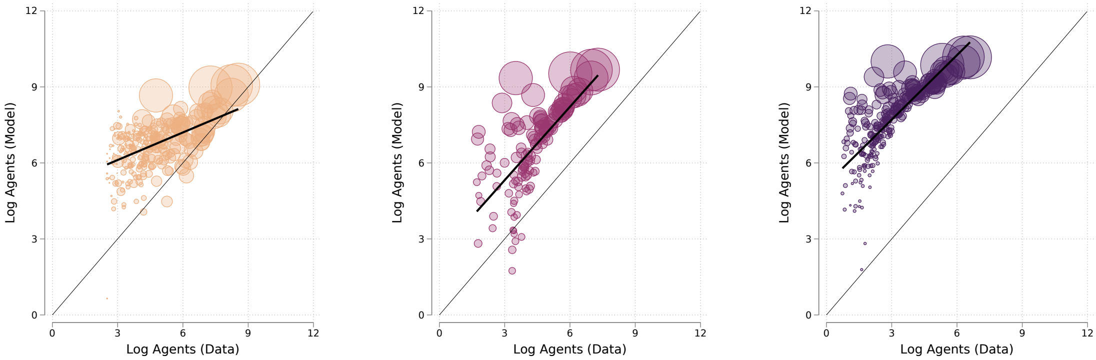
Sorting in the Estimated Model: Market Penetration



(a) Deciles 1-7 (b) Deciles 8-9 (c) Decile 10

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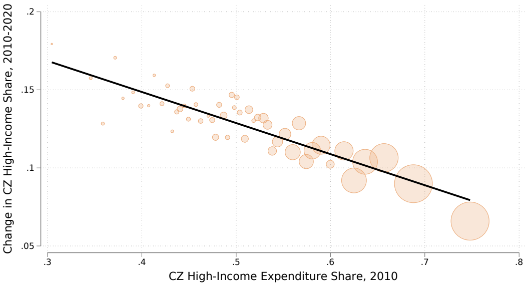
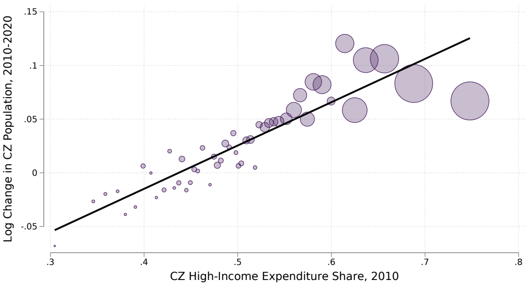
Testing the Model: Spatial Polarization

- How well does the model extrapolate to other settings?
- Explore the effect of changes in local fundamentals over the last decade
  - Poor places became **richer** but **smaller** relative to rich places in 2010
  - Compare change in total agents across commuting zones between 2010 and 2020





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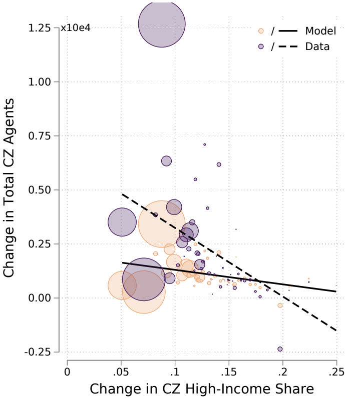
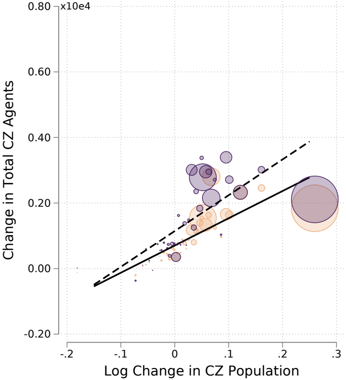
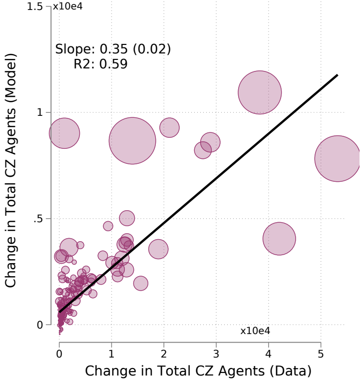
Testing the Model: Spatial Polarization



(a) High-Income Share



(b) Population



(c) Data

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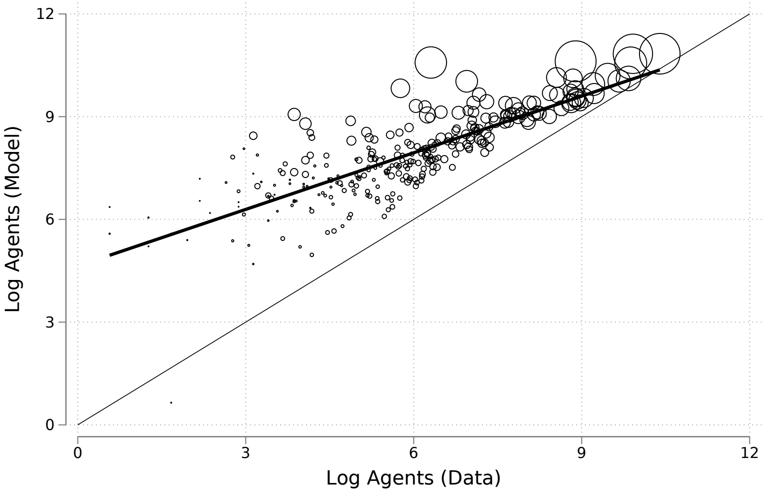
Estimation Results: Total Agents Across Markets



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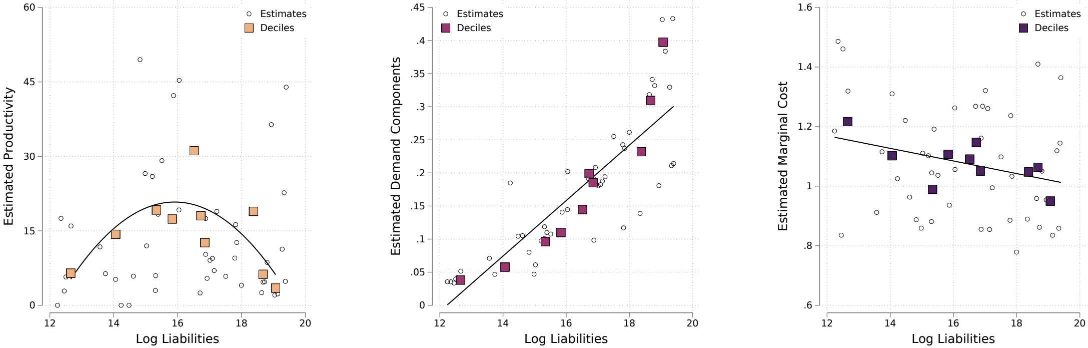
Estimation Results: Insurer Structural Parameters



(a) Productivity　(b) Demand Components　(c) Marginal Costs

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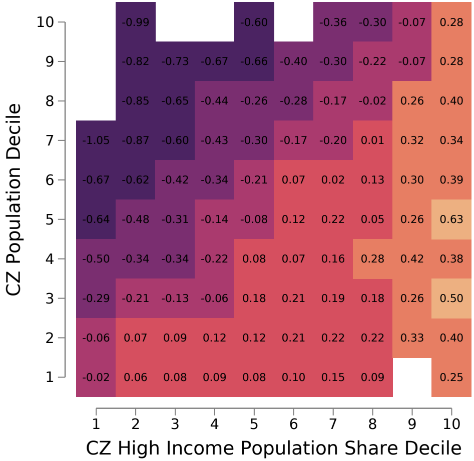
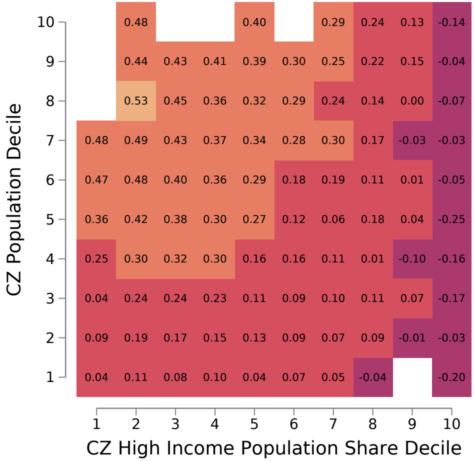
Baseline Welfare Effects by Income and Population



(a) Low-Income



(b) High-Income

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Which Firms Matter for Welfare Effects?

- What are the consequences of spatial sorting for local welfare effects?

- Useful to use the CS approximation and consider firm-level components:

$$\Delta CS_{js}^{k} \;\; \widetilde{\propto} \;\; \omega_j \left\{ \underbrace{\kappa_{js}^{\text{flex}} \left((p_j^{\text{natl}})^{1-\varepsilon_k} - (p_{js}^{\text{flex}})^{1-\varepsilon_k} \right)}_{\text{intensive margin}} + \underbrace{(p_j^{\text{natl}})^{1-\varepsilon_k} \left(\kappa_{js}^{\text{natl}} - \kappa_{js}^{\text{flex}} \right)}_{\text{extensive margin}} \right\}$$

- Crucial note: **intensive margin** $\rightarrow 0$ as $\kappa_{js}^{\text{flex}} \rightarrow 0$
  - **Extensive margin** most important for firms initially **sorting away** from a location;
  - **Intensive margin** most important for firms **sorting toward** a location
  - **Total effect** most important for firms with **large demand components**

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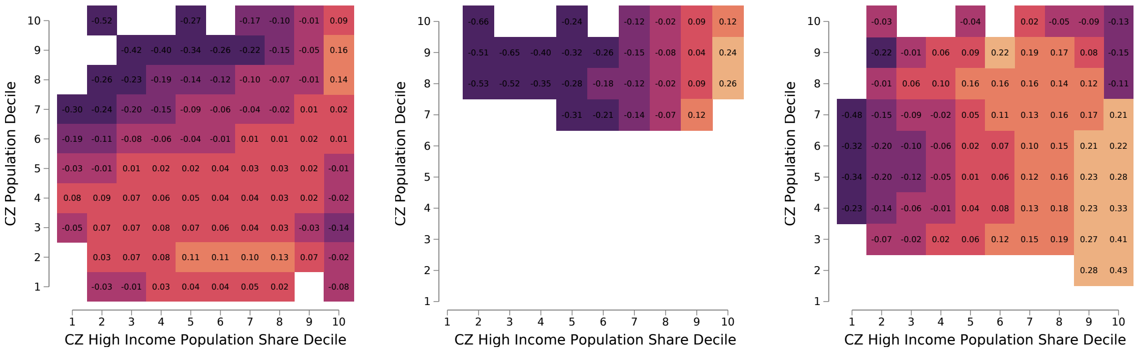
Which Firms Matter for Welfare Effects?



(a) Deciles 1-7 (b) Deciles 8-9 (c) Decile 10

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Details on Place-Based Policy

◇ For a given parameter tuple (q, μ_ℓ) with $\mu_\ell > 0$, consider the set of policies

$$t_s^*(q, \mu_\ell, \mu_h) = \begin{cases} (1+\mu_h)t_s, & \text{if } \eta_s \geq \eta_s^q \\ (1-\mu_\ell)t_s, & \text{if } \eta_s < \eta_s^q \end{cases} \quad \text{s.t.} \quad \int\int t_s^* S_{js}^* dj ds = \int\int t_s S_{js}^{\text{natl}} dj ds$$

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